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A Behavioral Approach to the Asset Allocation Puzzle

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Asset Allocation; Separation Theorem; Naive Diversification; Correlations; Behavioral Finance

This paper describes a study, in which we examine the diversification behavior of financial advisors. The Asset Allocation Puzzle describes the phenomenon that popular financial advice tends to be inconsistent with the mutual-fund separation theorem. While Canner, Mankiw and Weil (1997) try to explain the puzzle by relaxing the rigid assumptions of the CAPM, we follow another idea: Learning from Benartzi and Thaler (2000) about investors' naive diversification strategies, we find evidence that the Asset Allocation Puzzle can be explained by a new behavioral portfolio model. To verify these findings we distributed questionnaires among several investment consultants who gave us information about their market expectations and three asset allocation recommendations. Their recommendation strategies indeed seem to be reflected by the behavioral portfolio model. Finally, we examine losses of efficiency for their recommendations.

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1 Introduction

Talking about “strategic asset allocation” is a popular way for investment banks, insurance companies and financial advisors to discuss the “correct” proportions of several types of assets in the portfolio of an investor. “Types of assets” in this context could be short-term interest paying assets such as cash accounts and short-term bonds or long-term interest-paying assets such as bonds with longer durations. Other asset types could be different types of foreign and domestic stocks or stocks of blue chip and small cap companies. Even non-traded assets like real estate or antiques could be mentioned here.

From portfolio theory (Markowitz, 1952) and the Capital Asset Pricing Model, CAPM (Sharpe, 1964; Lintner, 1965 and Mossin, 1966), we learn how to determine the optimal proportions of these asset types in an investor’s portfolio if the μ-σ-principle holds. The μ-σ-principle describes a world where the expected return and the standard deviation (volatility) of the portfolio return are the only portfolio characteristics that influence investors’ utility. Given the expected returns, the standard deviations of the returns and the correlations between the assets, an optimal set of portfolios – called the efficient frontier – can be determined. It depends on the risk attitude of the investor which portfolio on the efficient frontier is chosen. One key result of this kind of rational decision making is that the portfolio should be a combination of a riskless asset and a risky portfolio the structure of which is independent of the investor’s risk attitude.

Because many investors need help and support in resolving their individual portfolio allocation problem they address employees of their retail bank or specialized investment consultants for advice. Usually investment advisors try to learn something about their clients’ risk attitude by asking them about their investment horizon, their age, their attitude towards losses, etc. before giving them some advice about the portfolio allocation[1]. They might even incorporate investor-specific expectations about return distributions into the analysis. Therefore – theoretically – it should be possible for each investment consultant to implement the rational

[1] An increasing number of countries require by law that investment advisors educate their clients about risk and also assess their clients’ risk attitude, see, e.g. in Germany No. 31(2) of the Wertpapierhandelsgesetz (WpHG).

model if the consultant (or the financial institution where he is employed) has clear ideas of the parameters “expected return”, “volatility” and “correlations” of each asset type and if the advisor knows his clients’ preferences regarding his portfolio risk and his portfolio return.

However, it is well known that investment advisors do not strictly follow the recommendations of portfolio theory. By far the majority of recommendations have the proportion of bonds versus stocks depending on the risk attitude of the investor. This violation of one of the key results of the capital asset pricing model has been named the “Asset Allocation Puzzle”. However, it should be pointed out (and we discuss it below in more detail) that the loss in efficiency due to incorrect recommendations is not very large (Canner, Mankiw and Weil 1997, hereafter CMW).

There have been quite a number of attempts to explain the asset allocation puzzle within the framework of portfolio theory. However, as we show in the next paragraph, none of these recent explanations is fully satisfactory. Here, we take a different angle to understand why advisors do not follow the recommendations of portfolio theory. We will present a new theory (called behavioral portfolio theory), which seeks to describe how individual investors intuitively perform asset allocation. We argue that investors take three aspects into account when creating an optimal portfolio: expected returns, pure risk and naive diversification. It will be shown that recommendations of investment advisors gathered from literature and by our own empirical study, are much closer to the results of behavioral portfolio theory than to the results of traditional portfolio theory. Thus investment advisor follow a strategy which might be quite clever: they do something “wrong” with respect to traditional portfolio theory, but which is quite appealing to the way their clients think intuitively, and the loss in efficiency due to following this behavioral theory is not so large.

Recently, the discussion about the asset allocation puzzle has intensified. CMW look at four of the investment recommendations of financial advisors, which are each given for three different risk attitudes: a conservative investor, a moderate investor, and an aggressive investor. As predicted by the asset allocation puzzle, the ratio between the recommended proportions of bonds and stocks is the smaller the higher the risk tolerance is. CMW try different ways to explain the puzzle, all within the framework of CAPM. Omitting the riskless asset they even get results pointing in the opposite direction. Using historical return distributions and assuming a constant relative risk aversion (CRRA) utility function cannot resolve the puzzle either. When short sales are restricted, the phenomenon of decreasing bond-to-stock ratios can partly be explained, but only in the domain where these restrictions are binding. A dynamic approach or the consideration of non-traded goods such as human capital and nominal debts could also help to explain the observed data, but CMW conclude in saying that there remains an open puzzle.

Brennan and Xia (1998) use a model of portfolio optimization in a dynamic context to explain the changing bond-to-stock ratios. As a possible reason for the violation of the separation theorem they find the fact that bonds co-vary negatively with expectations about future interest rates. Their model proposes that hedging considerations of the stochastic investment opportunity set might be the reason for the given allocation advice. Elton and Gruber (2000) concentrate on the historical data CMW used in their study. They show that – with or without short sale constraint – different historical data can lead to completely different optimal bond-to-stock ratios. Under reasonable assumptions they are able to find more recent market data that fit the observed portfolio recommendations. They propose, "that the advisor supply the input data on which suggested allocations are made"[2] to test the rationality of their recommendations. That is exactly what we will do in this study.

We follow a path different from staying within the framework of traditional portfolio optimization. That is because we refuse to believe that investment advisors and especially individual investors manage stochastic problems in the way the literature describes it. Like Shefrin and Statman (2000) we think about behavioral arguments that play a role for portfolio decisions. There is no reason not to believe that elements from behavioral research should be put forward if intuitive decision-making should be described.

The remainder of this paper is organized as follows. In section 2 we develop a behavioral approach to portfolio choice. Section 3 shows some basic properties of the new model. In section 4 we first compare the predictions of the behavioral model with the data provided

[2] See Elton and Gruber (2000), page 40.

in CMW and subsequently describe the results of our own study, which is based on investment advisors' recommendations. We also examine efficiency losses of these recommendations. Section 5 concludes this paper.

2 An Approach to Investor's Asset Allocation Strategy

Markowitz (1952) examines prescriptively, how to invest in several assets – given the expected returns, standard deviations and the correlations among the assets. He assumes the investors to be risk averse mean-variance-optimizers (μ-σ-principle), i.e. investors weigh up – according to their risk attitude – the advantages of more expected return of their portfolio (mean return) against the disadvantages of more portfolio risk, measured as the variance or standard deviation of the portfolio return. These assumptions are consistent with expected utility theory if investors' utility functions are quadratic or if returns are (log-) normal. The efficient mean-variance-frontier could be derived by maximizing expected portfolio return for each level of risk given (model opt1) or by minimizing expected portfolio risk for each level of return required (model opt2). To introduce notation, we present model opt1 below[3]:

<u>Model opt1:</u>

$$\underset{\alpha_i}{\mathrm{Max}} \sum_{i=1}^{n} \alpha_i \cdot \mu_i$$

s.t. $$\mathrm{Risk} = \sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n} \alpha_i \cdot \alpha_j \cdot \sigma_i \cdot \sigma_j \cdot \rho_{ij}} = \hat{r}$$

$$\sum_{i=1}^{n} \alpha_i = 1 \quad \text{and} \quad 0 \le \alpha_i \le 1 \; \forall \, i = 1,..,n$$

with n being the number of assets to choose from, α_i the proportion of asset i in the portfolio, σ_i the standard deviation (volatility) of asset i, μ_i the expected return of asset i and ρ_{ij} the

[3] To guarantee efficiency in these models it has to be checked that there are no portfolios that dominate the solution (α_i) (i.e. portfolios that have less risk but more expected return). In section 4.2 we will replace such dominated solutions by the "nearest" non-dominated solution.

correlation between the returns of asset i and asset j. We introduce a short sale constraint, as we do not believe that ordinary investors are willing to accept negative portfolio proportions[4].

Clearly, portfolio selection should be the basis for rational decision-making. However, it is also clear that subjects' intuitive asset allocations do not follow Markowitz' theory. There is experimental work, like e.g. Kroll, Levy and Rapoport (1988a and 1988b) and Weber and Camerer (1998), which shows that participants select their portfolios different from the theoretical approach. In addition, actual portfolio holdings and portfolio management are also quite different from portfolio theory (Blume and Friend, 1975; Kelly, 1994; Fisher and Statman 1997a, 1997b; Joos and Kilka, 1999; Benartzi, 1999 and Degeorge, Jenter, Moel and Tufano, 1999).

As pointed out in the introduction, the discrepancy between intuitive behavior and rational theory by itself is not surprising. Subjects will not be able to calculate an efficient frontier based on their individual expectations in their heads – this is exactly what investment advisors should help them to do. The key puzzle is that investment advisors are not communicating recommendations, which follow from portfolio theory, i.e. follow from the separation principle. Financial advisors, who are often employed by major banks, are the key impactors for investment decisions of private households. They are certainly able to implement the Markowitz model, but they also have to communicate the recommendations to their clients.

The behavioral portfolio model is based on three variables: expected return, pure risk and naive diversification. The main difference compared to the standard approach is the way risk is considered. We will show that there is ample evidence that subjects are very bad in dealing with correlations, nevertheless they are well aware that diversification is important in portfolio choice. It is therefore that risk should be broken down into two components:

- pure risk which will be defined as the (weighted) sum of risks of the different assets in the portfolio *without* considering correlations,

[4] See Elton and Gruber (2000), page 29: "Thus, an assumption of no short sales is the only realistic assumption for the asset allocation decision,…".

- naive diversification, which will capture the idea of diversification, implying that the investment should be spread quite even across the different types of assets.

We first discuss the variables in turn and than present the model[5].

Expected Return

We have no reason to believe that investors do not want to maximize expected return as in traditional portfolio theory as one of the variables they consider when defining an optimal portfolio:

$$\text{Expected Return:} \qquad \sum_{i=1}^{n} \alpha_i \cdot \mu_i \qquad \rightarrow \max$$

Pure Risk

Decision makers have some intuition about risk but they do not take correlations into account when making intuitive portfolio decisions. They determine the risk of a portfolio just by a linear combination of the risks of the assets or funds in the portfolio, i.e. they take all correlations to be 100%. Investors want to minimize the pure risk:

$$\text{Pure risk:} \qquad \sum_{i=1}^{n} \alpha_i \cdot \sigma_i \qquad \rightarrow \min$$

This assumption is supported by the literature on diversification behavior in financial experiments. In their studies Kroll, Levy and Rapoport (1988a and 1988b) and Weber and Camerer (1998) find that participants do not take correlations into account when making decisions about their portfolio. The same results can be found in Siebenmorgen, E.U. Weber and Weber (2000) who ask subjects to judge assets' volatility and risk. With his experiments, Oehler (1995)[6] gets similar results. His participants did not use the explicit information about the

[5] We are aware that the behavioral approach is no longer compatible with expected utility theory. However, Markowitz' approach is also only compatible under very restricted assumptions. In addition, we want to explore intuitive decision making on a portfolio level. On this level investors use heuristics (as proposed here) which are not compatible with expected utility theory.

[6] See section 3.3.3. in Oehler (1995).

correlations of investment alternatives to optimize their portfolios. In a questionnaire after his experiment the participants themselves ranked the correlations as the least important information for their decisions[7] [8]. The assumption gets further support by applying the idea of mental accounting (Thaler, 1985) to portfolio choice (see also Shefrin and Statman, 2000). If we regard each type of asset as a separate mental account, it is intuitive that correlations will not be considered.

It should be noted that this way of considering risk can only be a first step. Several extensions are possible. First, different measures of risk can be used. In this paper we stick to the measure, which is also used in traditional portfolio optimization[9]. However, other measures have been proposed to describe people's risk perception[10], some of which are even compatible with expected utility[11]. As a second extension, one could think of taking correlations to some degree into account, i.e. downgrading them by some specific factor.

Naive diversification

Even if subjects do not take correlations into account, they nevertheless like the idea of diversification. Investors tend towards "naive diversification", i.e. investors want to split their wealth evenly among several investment alternatives – perhaps because they have learned about the advantages of diversification or perhaps because they intuitively behave like this. Naive diversification is operationalized here by the standard deviation of the asset proportions α_i .

[7] See also section 6.3.3 in Schroeder-Wildberg (1998).

[8] It should be noted that there are few studies that find some effect of correlations on portfolio choice. Kroll and Levy (1992) find *some* effects driven by correlations between different investment options. In their new experimental design they offered more attractive incentives to the students, who were highly educated MBA students. Furthermore, they published the results and strategies of all students after each round. So, the participants had the possibility of learning and imitating successful strategies.

[9] Alternatively, we used the linear combination of the variance of the assets ($\sum_{i=1}^{n} \alpha_i \cdot \sigma_i^2$) as measure for pure risk, but we did not find different results.

[10] See E.U. Weber (2000).

[11] See Weber (2000).

Diversification[12]: $\mathrm{Std}(\alpha_1,\ldots,\alpha_n) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\alpha_i - \overline{\alpha})^2} \rightarrow \min$

Benartzi and Thaler (2000) examine the behavior of "naive diversification". This means that investors tend to distribute their capital evenly among the available investment alternatives[13]. Asking employees of the University of California for their allocation of retirement contributions, Benartzi and Thaler show that their asset selection and therefore the risk they accept in their portfolio strongly depends on the type of assets that are offered to them. If being offered a fund of stocks and a mixed fund of stocks and bonds, people tend to invest significantly more in stocks compared to the situation in which they are offered a mixed fund and a fund just containing bonds[14]. In the same paper an empirical study of several contribution plans in the United States confirms this behavior, as the average allocation to equities strongly depends on the relative number of equity-type investment options.

Fisher and Statman (1997a and 1997b) also find evidence for naive diversification in their study. People tend to "split" their wealth by investing into all available assets or funds without thinking about the optimal diversification strategy. The authors also show that the allocations of mutual funds and the guidelines for fiduciaries (called ERISA) are closer to naive diversification than to the optimal diversification described by Markowitz. A similar behavior called "variety seeking" was found by Read and Loewenstein (1995) in an earlier experiment even among children. In one condition of their experiment (at Halloween), in which children had to choose one candy in two different situations, they decided to take the same candy twice. When offering the children two candies at the same time, however, they tended to choose two different candies. So additionally, there seems to be an instinctive tendency "not to put all eggs in one basket".

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[12] Notice that for the mean proportion holds: $\overline{\alpha} = \frac{1}{n}\underbrace{\sum_{i=1}^{n}\alpha_i}_{=1} = \frac{1}{n}$.

[13] Benartzi and Thaler mention that the "1/n heuristic" or "1/n rule" even goes back to the 4th century, when this rule had been proposed in the "Babalonian Talmud".

[14] This effect is not driven by the restrictions of investors' investment alternatives.

Behavioral Portfolio Model

We assume that our agents try to optimize their portfolio strategy by searching asset allocations that are on the efficient frontier of these three target variables. To be able to compare the traditional approach with this approach we propose alternative models. In these models we define – as in the Markowitz model – one target function and one restriction using these three target variables. To do this we combine (linearly) two of the three target variables. Consequently, there are six possiblities (see Table 1) to build a behavioral model using these three target variables:

Model	**restriction:**	**target function:**
M1	Expected Return	linear combination of Diversification and Pure Risk
M1b	linear combination of Diversification and Pure Risk	Expected Return
M2	Pure Risk	linear combination of Expected Return and Diversification
M2b	linear combination of Expected Return and Diversification	Pure Risk
M3	Diversification	linear combination of Expected Return and Pure Risk
M3b	linear combination of Expected Return and Pure Risk	Diversification

Table 1: Possible behavioral models

We will test our models using recommendation data of financial advisors. We will do this by restricting the models to the actual characteristics of the given recommendations. For model M1, e.g., we will calculate the expected returns of the given recommendations and will use these values in the restriction of model M1. Keeping these values fixed we have to maximize or minimize the target function. This procedure generates benchmark portfolios, which we compare with the actual recommendations.

The advisors' and investors' intention when thinking about an adequate portfolio strategy is not only the efficiency of the portfolio. They also have to consider their own or their clients' risk attitude and the returns they expect. In order to generate reasonable benchmark portfolios we have to choose those models that are able to fix these characteristics of a given portfolio recommendation. Consequently, as the restricitions of models M1b, M2b and M3 contain the term "Diversification", these models cannot be used to build a benchmark portfolio for the recommended asset allocations. They would generate portfolio solutions with completely different pure risks or expected returns[15]. We will therefore investigate models M1 and M2 as reasonable behavioral models[16]. M2 will be our primary model, as it ensures that the behavioral benchmark portfolio will have the same (pure) risk as the recommended portfolio. In model M1 people might restrict their portfolio choice by a certain amount of expected return.

Model M1 determines – for each value of expected return $\hat{e}$ – a portfolio that is optimal regarding diversification and pure risk. We do this by defining a target function that combines the two variables Diversification and Pure Risk using a linear function:

Model M1(β): $\beta \in [0;1]$

$$\min_{\alpha_i} \beta \cdot \text{Diversification} + (1-\beta) \cdot \text{Pure Risk}$$

s.t. Expected Return $= \hat{e}$

$$\sum_{i=1}^{n} \alpha_i = 1 \quad \text{and} \quad 0 \le \alpha_i \le 1 \; \forall\, i = 1,..,n$$

Model M2 assumes that investors restrict their portfolio decisions to a certain amount of pure risk $\hat{r}$. Given this constant amount of pure risk they maximize a linear combination of the target variables Expected Return and Diversification:

Model M2(γ): $\gamma \in [0;1]$

$$\max_{\alpha_i} \gamma \cdot \text{Expected Return} - (1-\gamma) \cdot \text{Diversification}$$

s.t. Pure Risk $= \hat{r}$

$$\sum_{i=1}^{n} \alpha_i = 1 \quad \text{and} \quad 0 \le \alpha_i \le 1 \; \forall\, i = 1,..,n$$

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[15] The application of these models to recommendations for three different risk attitudes (see section 4) shows that the (pure) risk of the three generated benchmark portfolios often changes its order, e.g. the benchmark portfolio of the riskiest recommendation is less risky than the benchmark portfolios of the other recommendations. Therefore these models are not appropriate.

[16] Model M3b would also be an appropriate model, as its restriction contains a linear combination of the pure risk and the expected return of the portfolio. For model M3b we indeed find similar results as for models M1 and M2, but they will not be presented in the following sections.

3 Properties of the Behavioral Portfolio Model M2

In this section we will examine model M2 by illustrating some of its properties[17]. We use the historical data (see appendix E) of five popular asset classes for German investors:

"short-term"	cash, money market funds or short-term bonds (TTM[18]<1 year) denoted in Euro
"bonds"	bonds with TTM between 5 and 20 years denoted in Euro
"blue chips"	30 German stocks, which belong to the most important German stock index DAX or funds that invest in the DAX
"small caps"	smaller German stocks
"foreign stocks"	investments in foreign stocks

Most financial advisors in Germany use these asset classes (or similar classifications of the available investments) when they talk about "asset allocation" to their clients. Consequently, it is interesting to compare the results of the behavioral model M2 with those of the rational Markowitz model using these investment alternatives.

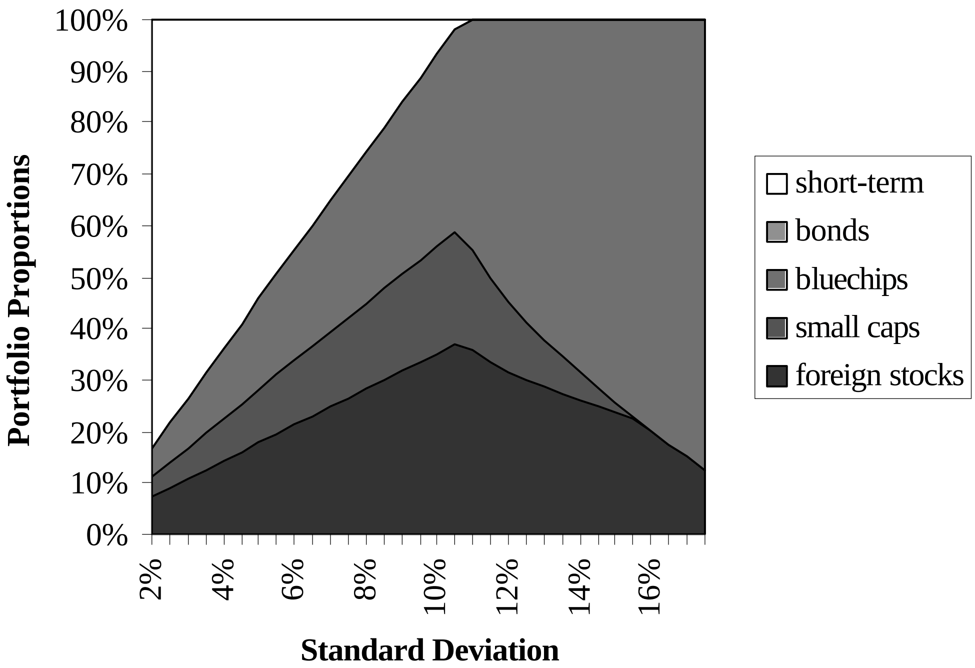

Figure 1: Asset proportions for the Markowitz model

[17] For model M1 we find similar properties.

[18] time to maturity

Figure 1 shows the optimal portfolio proportions of the Markowitz model, based on historical correlations between the five asset classes. The horizontal axis denotes the standard deviation of the portfolio return (volatility), while the vertical axis illustrates the percentages of the five different asset classes. Consequently, Figure 1 shows the optimal portfolio proportions depending on different risk attitudes, i.e. degrees of risk aversion.

According to this model and based on the data from 1988 to 1999 the asset class "bonds" has to have a percentage of 0% for each risk attitude. The less risk averse the investors are, the higher the proportion of stocks in this model, which seems quite reasonable. But because of the short sale constraint the percentages of small caps and foreign stocks are not monotonous. Figure 2 shows the efficient frontier in a Standard Deviation-Expected Return-diagram.

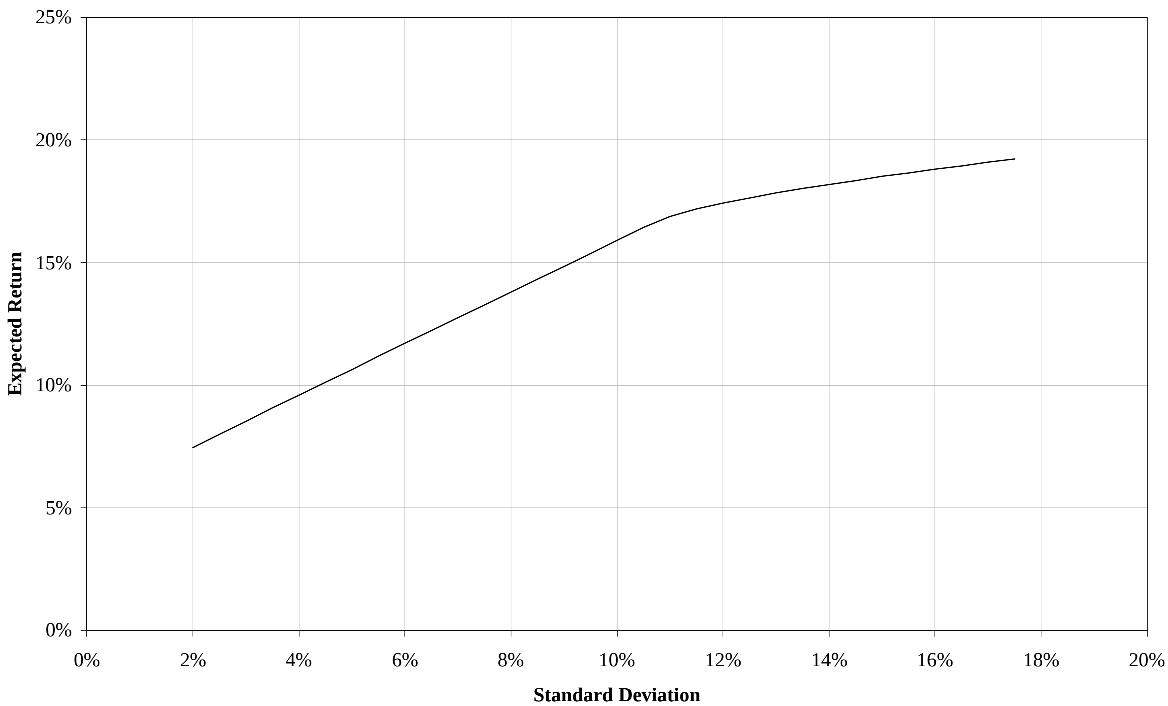

Figure 2: Efficient frontier for the Markowitz model

The parameter γ in model M2 (and β in M1) capture the weighting of the two target variables in the target function. This weighting surely is an investor- or advisor-specific parameter which could be estimated separately for each person. Furthermore, it probably depends on n, as n influences the measure of diversification. We start our analysis with γ=0.5 and do some sensitivity analysis later. Model M2(0.5) seems to be capable of capturing investors' or advisors' diversification behavior, as it proposes a positive and decreasing proportion of bonds in the portfolios. Figure 3 shows the proportions of the five asset classes depending on pure risk. The less risk averse the investors are, i.e. the less pure risk s/he is willing to take, the higher the percentage of stocks in this model.

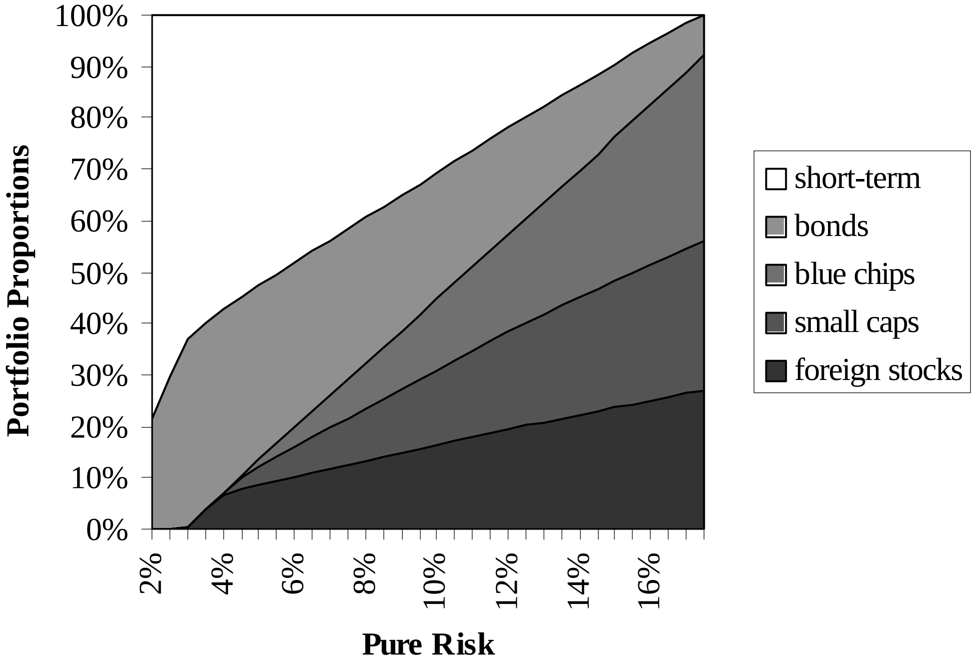

Figure 3: Portfolio proportions of model M2(0.5)

Figure 4 illustrates a specific property of model M2(γ) for γ < 0.81: the efficient frontier is not monotonous. Therefore, an investor who decides about his portfolio should never accept (pure) portfolio risk that is above approx. 12.5% – the pure risk of a 1/n-portfolio which divides investors' wealth evenly among the five asset classes (20% for each asset class). Because the efficient frontier is decreasing above this value, portfolios with pure risk above this value are dominated by the 1/n-portfolio. To explain such dominated solutions descriptively, we necessarily need the "=" in the restriction "Pure = $\hat{r}$" of our behavioral model. This means that investors or their advisors restrict their portfolio allocation to a certain amount of fixed pure risk and optimize the target variable (linear combination of Expected Return and Diversification). An explanation why investors or their advisors might behave like this could be that they look for portfolios that have a high level of pure risk because they associate a certain amount of expected return with this level of pure risk. Therefore they might be willing to accept more pure risk than the pure risk of the 1/n-portfolio.

It is important to realize that dominated solutions in such two-dimensional spaces are not necessarily dominated solutions in the original three-dimensional space (for $\gamma > 0$). If expected return and risk of the available assets are positively correlated[19], the solutions with more pure risk than the 1/n-portfolio tend to have more expected return. As a result, such risky portfolios are not dominated in the three-dimensional space of the three original target variables "Expected Return", "Pure Risk" and "Diversification".

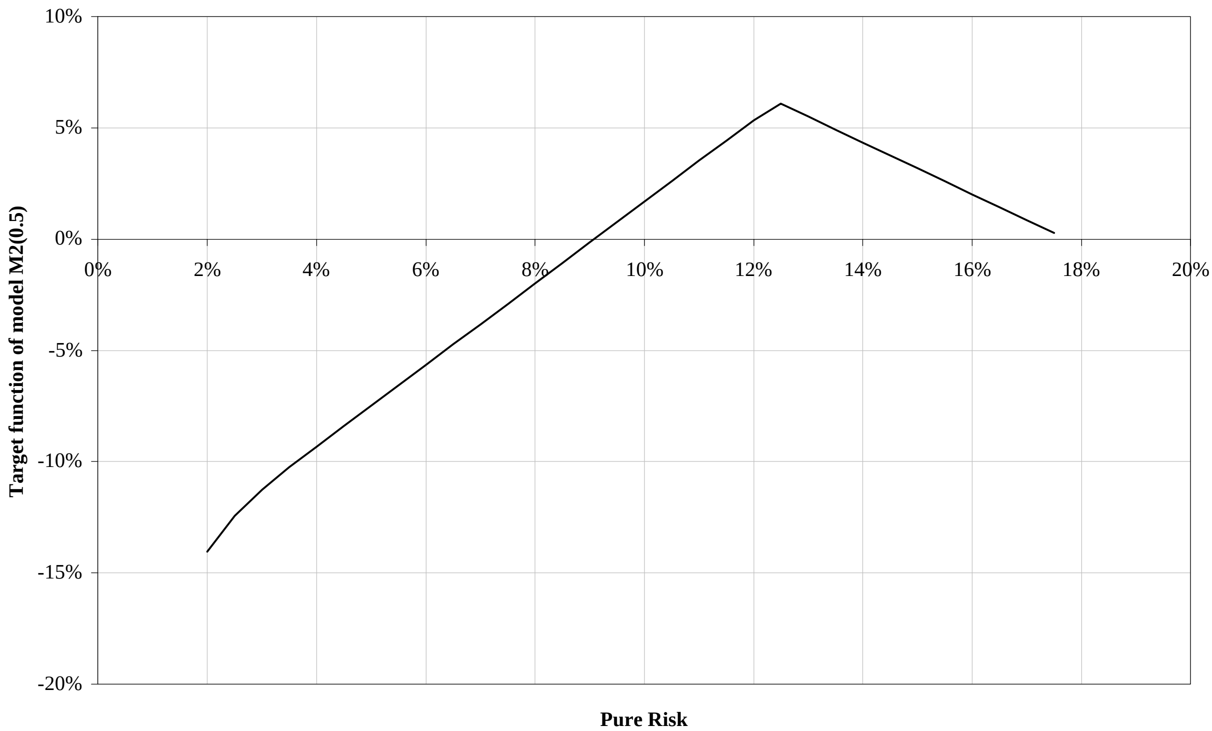

Figure 4: Efficient frontier of model M2(0.5)

19 This is exactly what we find in our data.

For $\gamma > 0.81$ the model puts more weight on the expected return and therefore does not generate dominated solutions in the two-dimensional space. Figure 5 shows the portfolio proportions of model M2(0.9). Figure 6 presents the corresponding efficient frontier, which is monotonously increasing. In this case, an investor who only thinks about pure risk and the objective function of M2(γ) would also accept more pure risk than the pure risk of a portfolio which allocates the money evenly among the five asset classes (1/n-portfolio).

The examination of all parameters $\gamma \in [0,1]$ shows that as long as there is enough weight on the term “Diversification” in the target function (i.e. γ is substantially below 1), the portfolio proportions differ slightly from those of the model M2(0.5). There are some differences regarding the proportions of foreign stocks and small caps, but the relation between stocks and bonds remains the same. For γ=1 or near 1, however, we find completely different portfolio proportions because in model M2(1) the investors look for those investments with the best return-risk-ratios and take only these into their portfolio by restricting themselves to the given amount of risk.

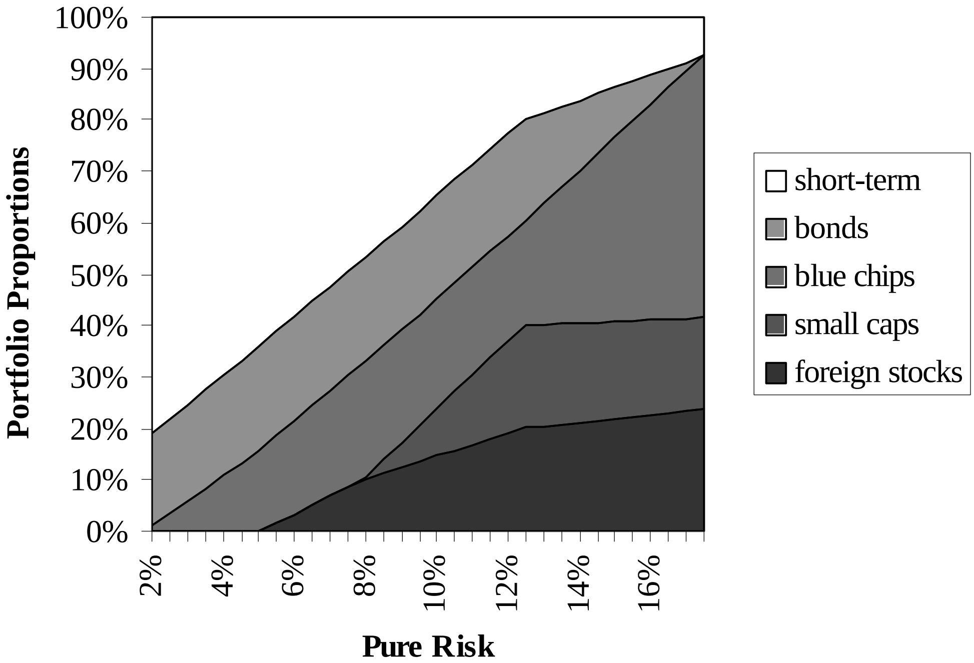

Figure 5: Portfolio proportions of model M2(0.9)

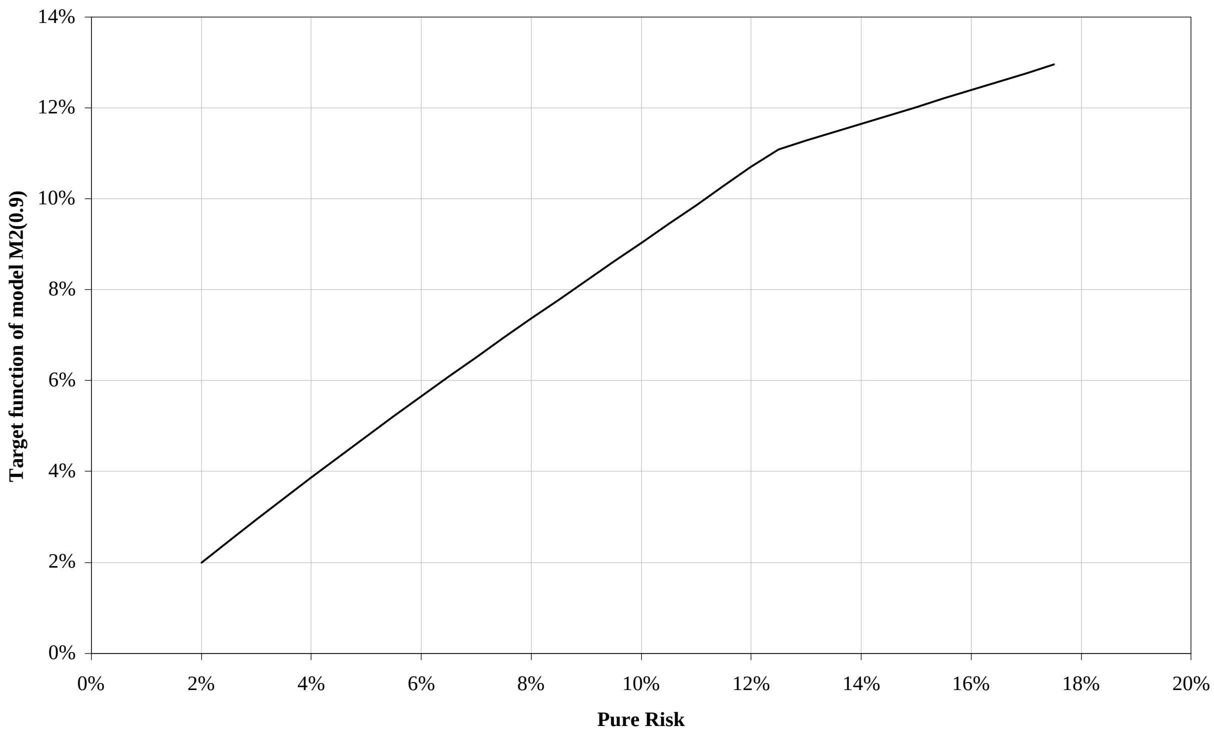

Figure 6: Efficient frontier of model M2(0.9)

After this first investigation of the behavioral model M2, we will now test if it can explain real world recommendations of financial advisors. In section 4.1 the model is tested based on the data presented in CMW and in section 4.2 based on recommendations of German investment advisors.

Given the historical data in Germany, we do not find major differences regarding the parameters. We will use γ=0.5 (and β=0.5) in the remainder of this paper to test the validity of our models. Furthermore, we will examine the model M2(0) to examine the role of the expected returns. In section 4.2 we will also add an evaluation, in which we will only accept non-dominated solutions.

4 A Key to the Asset Allocation Puzzle ?

4.1 Explaining the investment recommendations in CMW

To be able to compare the recommendations of the behavioral model with the investment advice of the financial analysts in CMW, we take the same (historical) data of the three asset types (n=3) "stocks", "bonds" and "cash" as given in their study:

i	**Asset**	μ_i	σ_i	**correlation with bonds**	**correlation with stocks**
1	Cash	0.6 %	4.3 %	0.63	0.09
2	Bonds	2.1 %	10.1 %	1.00	0.23
3	Stocks	9.0 %	20.8 %	0.23	1.00

Table 2: Historical market data from 1926 to 1992 (see CMW)

To get first insights into the descriptive quality of the behavioral models, we solve for the optimal values of α_i using model M2 with parameter $\gamma = 0.5$[20] for different values of pure risk $\hat{r}$. The resulting portfolio proportions are presented in Figure 7.

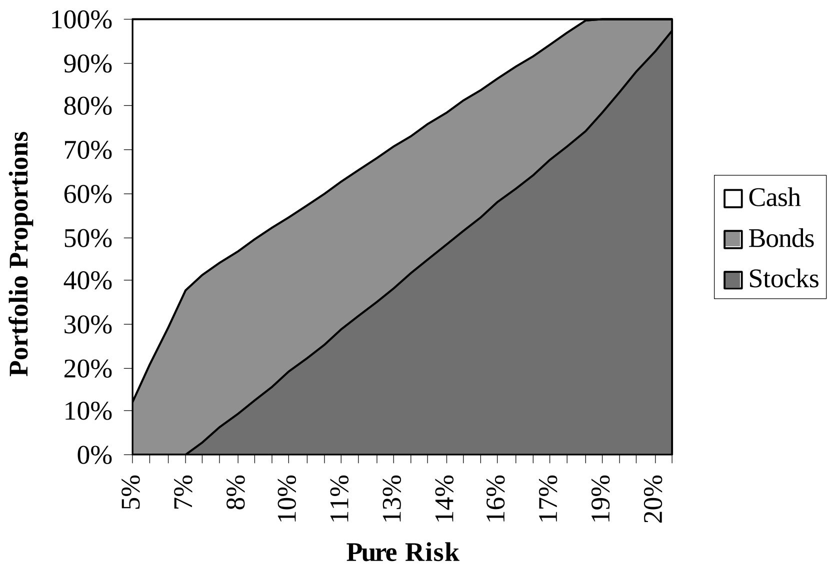

Figure 7: Portfolio proportions using model M2(0.5)

[20] We get nearly the same results if we take other parameters $\gamma < 1$ or if we use model M1 with $\beta > 0$.

In Figure 8 we plot the bond-to-stock-ratio of model M2 against the stock proportion of the portfolio as it is done in the CMW study[21].

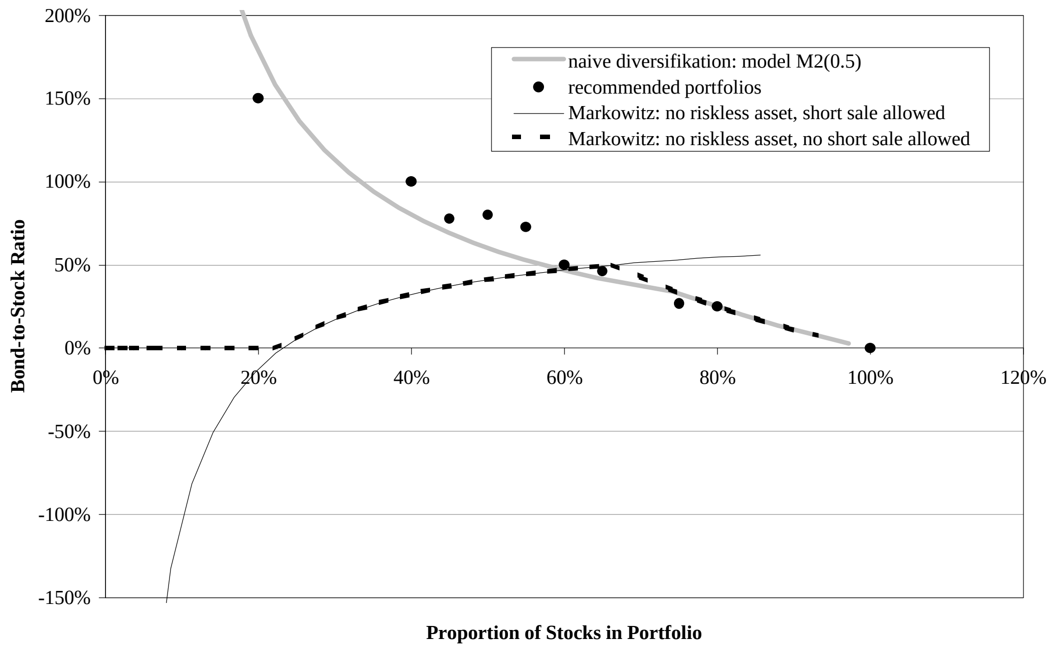

Figure 8: Bond-to-stock ratios

The thin line is already shown in the study of CMW. It illustrates the optimal portfolios for the case without riskless asset and without a short sale constraint. The central question of the Asset Allocation Puzzle is why the recommended portfolios (big dots) show a decreasing tendency of the bond-to-stock-ratio in the proportion of stocks while the optimal portfolios show an increasing tendency. CMW find that the short sale constraint partially explains the puzzle: The thick dotted line shows that in the high-risk-area the bond-to-stock-ratios of the recommended portfolios coincide with the ratios of optimal portfolios if short sales are not allowed. But in the low-risk-area the portfolios based on the optimal (Markowitz) portfolios still do not fit the observed recommended portfolios. The behavioral models (here model M2(0.5) - thick

[21] Canner, Mankiw and Weil (1997), page 184.

gray line) fit the given recommendations quite well: The bond-to-stock ratio shows a decreasing tendency for all stock proportions.

Alternatively, we try to use Markowitz' way to illustrate the optimal portfolio proportions α_i to compare his results with our approach. In his study he also investigates the 3-asset-case (n=3) and plots the optimal α_1 and α_2 (α_3 is given by $\alpha_3 = 1 - \alpha_1 - \alpha_2$) in a two-dimensional diagram. Figure 9 illustrates the Markowitz-optimal portfolios and the portfolios based on model M2(0.5) for the data presented in CMW. The large triangle is the set which Markowitz calls the "attainable set", which includes all portfolios without short sales. The dotted lines show the optimal portfolios Markowitz prescribes. The solid line shows the results based on our model. The thin lines allow for short sales and the thick lines show the portfolios restricted by the short sale constraint. The big dots in the diagram show the recommended portfolios of the four analysts, CMW present. Again it is obvious, that the naive diversification model describes the investment behavior (or – to be precise – the investment advice of financial analysts) better. In the more risk averse domain, the diagram confirms that investors tend to hold relatively more bonds than Markowitz would prescribe.

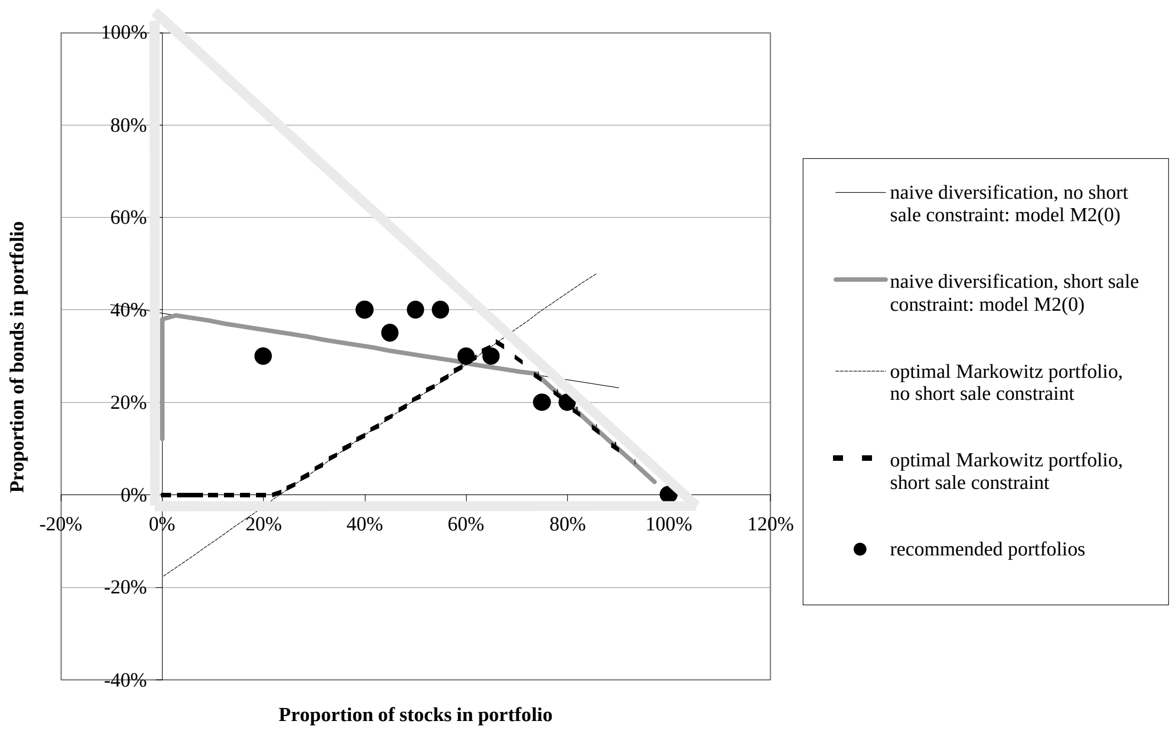

Figure 9: Proportion of bonds against Proportion of stocks

4.2 A Study among Bank Employees

To compare the normative and the behavioral portfolio selection models more profoundly we gathered data from bank's investment advisors in the southwest of Germany (Frankfurt, Stuttgart, Mannheim, Heidelberg, Speyer, Karlsruhe, Offenburg and Freiburg). Most private investors in Germany ask their bank to give advice on their investment decisions. They rarely use brokerage firms that do not offer any investment recommendations, to get access to the financial markets. Therefore well-educated and well-informed bank employees in Germany have a decisive influence on private investors' portfolio decisions. For that we visited consultants of the departments "Private Banking" who are used to managing portfolios of at least DM 100,000. This way we reach the highly professional advisors who have millions of Deutschmarks of funds under management and asked them for their recommended asset allocations for different risk attitudes. Furthermore, we asked them for their market expectations. By linking the experts' market expectations with their preferred asset allocations we hope to learn more about the advisors' diversification behavior[22].

Method

Our questionnaire consisted of four pages (see appendix A to D). It began with a short introduction simply telling that we intend to study recommended portfolios of bank employees and investment consultants. Then we presented the consultants three fictive new clients. Each of them is 26 years old, not married and without any savings. They have just finished their master in business administration at the university of Mannheim and will inherit DM 500,000 (approx. $ 250,000) within the next days. None of them know when they will need parts of their new wealth but they have different risk attitudes: They prefer conservative: C, moderate: M and aggressive: A, investment strategies respectively. We asked the participants of our study to recommend an asset allocation for each of the three fictive clients, being only allowed to choose from the asset types presented in section 3 (short-term, bonds, blue chips, small caps and foreign stocks).

[22] We got answers from employees of all major German banks. For reasons of confidentiality we will not mention their names explicitly.

In the second part of the questionnaire we elicited the consultants' market expectations for the given five asset classes and for the three recommended portfolios. We asked for a median estimate and estimates for an upper bound (90%-quantile) and a lower bound (10%-quantile) of the one-year returns. Finally, we asked them to estimate the ten correlations between each of the five asset types by marking a scale from –100% to +100%. Clemen, Fischer and Winkler (2000) show that this method is appropriate to get good dependence assessments of participants[23].

From January to May 2000 we distributed 51 questionnaires in the southwest of Germany. In each city we only dropped one questionnaire in each bank to reach the highest possible independence in our data. 5 consultants refused to answer our request. Another 4 questionnaires were not returned as consultants of the same banks but from different cities sent them to their headquarters (public-relations-department), from where we only received one joint response[24]. 3 questionnaires got lost. 10 bank employees did not send the questionnaire back, although they had promised to answer the questions and although they were reminded several times. So we received 29 questionnaires back (56.9%). 6 of which showed incomplete[25] or inconsistent[26] data and were therefore not useable. Consequently, we remained with 23 completed questionnaires for our evaluations.

Results

Appendix E and F show the mean market expectations[27] and the mean portfolio recommendations of our participants. The tables show that the investment consultants have reasonable market expectations. Asked directly for the correlations between the five asset classes they are able to give good estimates that do not differ very much from the historical correlations. On

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[23] See also Clemen and Reilly (1999).

[24] Examining in particular these questionnaires we do not get different results.

[25] Some consultants added some additional investment alternatives to their recommendations. As we do not know their market expectations about these additional investments we cannot use the answers.

[26] In one case the variance-covariance-matrix resulting from the given answers is not positive semi-definit, which led to a negative variance of one portfolio. Therefore we could not use these answers.

[27] To estimate the expected returns and the volatilities with the stated 10%-quantile, the 90%-quantile and the median we used the three-point estimator of Pearson and Tukey (as described in Keefer and Bodily, 1983).

average our participants estimated the volatility of the short-term investment to be 0.6% (historical volatility: 0.7%). In their study CMW distinguish between the two cases with or without a riskless asset (volatility of 0%). Because of the low estimated short-term volatilities we will not consider a riskless asset in our analysis[28].

To learn more about the mechanism of portfolio selection our data enable us to test the behavioral portfolio model. We first check the assumptions of behavioral portfolio theory "only considering pure risk, i.e. neglecting correlations" and then test the model via its portfolio predictions. The assumption about "naive diversification" cannot be tested directly via our data.

We begin with investigating if correlation effects are neglected when people judge portfolio risks. For each participant k we compare the assessed volatility of the recommended portfolios for conservative (σ_k^C), moderate (σ_k^M) and aggressive investors (σ_k^A) with the implicit volatility $\hat{\sigma}_k^C$, $\hat{\sigma}_k^M$ and $\hat{\sigma}_k^A$ using the individual market expectations of the five asset types and the given portfolio recommendations $\alpha_{i,k}^C$, $\alpha_{i,k}^M$ and $\alpha_{i,k}^A$:

$$\hat{\sigma}_k^C = \sqrt{\sum_{i=1}^{n=5}\sum_{j=1}^{n=5} \alpha_{i,k}^C \cdot \alpha_{j,k}^C \cdot \sigma_{i,k} \cdot \sigma_{j,k} \cdot \rho_{ij,k}} \qquad \text{(similarly for } \hat{\sigma}_k^M \text{ and } \hat{\sigma}_k^A\text{)}$$

We find that the assessed volatilities σ_k^C, σ_k^M and σ_k^A tend to be overestimated (see average and median values in Table 3). The assessed volatilities are for all portfolio types significantly above the implicit volatilities calculated by using the given correlations (Wilcoxon-test: low risk: p=0.002**, moderate risk: p=0.003**, high risk: p=0.000**). So, diversification effects are underestimated[29].

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[28] We recalculated our results by assuming the short-term volatility to be 0% and we did not find other results.

[29] This confirms a result regarding diversification effects in Siebenmorgen, E.U. Weber and Weber (2000). There we asked students who participated in a risk perception experiment to estimate volatility and risk of diversified portfolios and we found that volatility and risk of these portfolios tended to be overestimated relatively to the individual assets.

Alternatively, we calculate for each participant k and each portfolio recommendation (C, M or A) the "pure risks" $\tilde{\sigma}_k^C$, $\tilde{\sigma}_k^M$ and $\tilde{\sigma}_k^A$ that are generated by assuming all correlations to be 100%:

$$\tilde{\sigma}_k^C = \sum_{i=1}^{n=5} \alpha_{i,k}^C \cdot \sigma_{i,k} \qquad \text{(similarly for } \hat{\sigma}_k^M \text{ and } \hat{\sigma}_k^A\text{)}$$

We find that the assessed volatilities even tend to be above the values of pure risk, although the difference is only significant for the aggressive portfolio (Wilcoxon-test: p=0.855, p=0.693, p=0.009**). Table 3 shows the mean and median values for each portfolio type.

mean (median)	**low risk (C)**		**moderate risk (M)**		**high risk (A)**	
assessed volatilities	σ_k^C	3.40% (2.72%)	σ_k^M	6.08% (5.32)	σ_k^A	11.08% (9.50%)
implicit volatilities	$\hat{\sigma}_k^C$	2.40% (1.92%)	$\hat{\sigma}_k^M$	4.47% (3.95%)	$\hat{\sigma}_k^A$	7.09% (5.94%)
pure risk	$\tilde{\sigma}_k^C$	3.49% (2.68%)	$\tilde{\sigma}_k^M$	5.90% (4.77%)	$\tilde{\sigma}_k^A$	8.68% (7.00%)

Table 3: Assessed and implicit volatilities and pure risk

These results clearly indicate, that correlation effects cannot explain the assessed volatilities. The assumptions that people use pure risk, however, are compatible with the data.

We now want to test if the traditional theory or the behavioral approach presented above is better able to explain the portfolio recommendations we collected. We will compare the behavioral models M1 and M2 with the Markowitz models opt1 and opt2. To implement the models opt2 and M1 we take the expected returns of the recommended portfolios as $\hat{e}$ and restrict the models to this expected return $\hat{e}$. Similarly, we take the observed volatility/pure risk of the recommended portfolios as $\hat{r}$ to implement the models opt1 and M2. The following distance measure will be used to compare the two types of models[30]. This quadratic dis-

[30] Kroll, Levy and Rapoport (1988b) use a similar measure.

tance measure simply determines the distance between a model and the recommended portfolio.

$$DM_k^C = \sqrt{\sum_{i=1}^{5}\left(\hat{\alpha}_{i,k}^C - \alpha_{i,k}^C\right)^2} \qquad \text{(similarly for } DM_k^M \text{ and } DM_k^A\text{)}$$

$\hat{\alpha}_{i,k}^C$, $\hat{\alpha}_{i,k}^M$ and $\hat{\alpha}_{i,k}^A$ denote the predicted portfolio proportions of the models.

Comparing the distance measures for several models we find significant differences. Using the Markowitz models opt1 or opt2 we measure a higher distance than using the behavioral models M1 and M2 with the chosen parameters β=0.5, γ=0 and γ=0.5. Table 4 shows the mean and median results for the three risk classes C, M and A and the five different models we compare. The last column shows the average distance measures over all risk classes[31].

mean (median)	**low risk (C)**	**moderate risk (M)**	**high risk (A)**	**average**
opt1	52.5% (45.6%)	42.2% (43.0%)	37.4% (40.8%)	44.0% (43.0%)
opt2	53.7% (48.7%)	45.1% (48.2%)	42.6% (43.3%)	47.1% (47.7%)
M1(0.5)	33.9% (33.0%)	22.2% (20.0%)	19.9% (22.1%)	25.4% (24.7%)
M2(0)	33.9% (32.5%)	22.2% (19.8%)	22.4% (22.0%)	26.2% (24.6%)
M2(0.5)	33.3% (32.3%)	21.8% (19.2%)	21.8% (22.0%)	25.6% (25.2%)

Table 4: Distance measures between models and recommendations

When we look at the non-aggregated individual data of the investment consultants we find for 20 out of 23 consultants that the behavioral models describe their behavior more appropriately than the optimal models. Table 5 shows the results for the models opt1 and M2(0.5)[32] averaged over the three risk categories. The differences of those participants whose behavior is better described by the optimal model opt1 than by the behavioral model M2(0.5) are highlighted.

[31] The models opt1 and opt2 differ as they generate different benchmark portfolios on the efficient frontier.

[32] Using opt2 instead of opt1 or M1(0.5) resp. M2(0) instead of M2(0.5) does not change the results substantially.

Participant	Opt1	M2(0.5)	Difference
1	52.25%	9.10%	43.15%
2	42.96%	25.46%	17.50%
3	26.14%	17.49%	8.65%
4	56.26%	39.14%	17.12%
5	62.09%	34.61%	27.48%
6	50.93%	26.53%	24.41%
7	60.26%	24.02%	36.25%
8	41.97%	15.42%	26.55%
9	37.40%	25.57%	11.83%
10	73.11%	24.24%	48.87%
11	51.91%	37.57%	14.34%
12	64.19%	42.77%	21.42%
13	27.80%	24.56%	3.24%
14	27.58%	29.77%	-2.19%
15	42.17%	22.17%	20.00%
16	49.74%	32.51%	17.23%
17	51.60%	21.15%	30.45%
18	38.80%	24.60%	14.20%
19	27.08%	30.06%	-2.98%
20	44.94%	11.95%	33.00%
21	14.36%	40.13%	-25.78%
22	39.12%	13.75%	25.37%
23	27.79%	17.68%	10.11%

Table 5: Non-aggregated results for model opt1 and M2(0.5)

We use a Wilcoxon-test[33] to compare the two classical approaches opt1 and opt2 with our three behavioral approaches M1(0.5), M2(0) and M2(0.5). Table 6 shows the p-values for the hypotheses that the distance measures of the behavioral models M1(0.5), M2(0) or M2(0.5)[34] are equal to the distance measures of the rational models opt1 or opt2. The comparisons are based on the average distance measures of the three types of portfolios[35]. These results show

[33] We get the same results for a paired-samples T-test.

[34] In a sensitivity check we controlled the influences of the parameters β and γ in the models M1 and M2 and we found a very low sensitivity. But for the cases β=0 and γ=1, in which the target variable “diversification” disappears, the behavioral models are not better than the optimal models any more.

[35] If we test the three risk classes individually, we also get significant results for all combinations.

significantly that our new approaches seem to be a better descriptive model of the experts' recommendation behavior. It indeed seems to be the case that even well-educated and well-informed investment professionals do not think about correlations but diversify by using a naive heuristic.

		M1(0.5)	**M2(0)**	**M2(0.5)**
average distances over all portfolios	opt1	p=0.000 **	p=0.000 **	p=0.000 **
	opt2	p=0.000 **	p=0.000 **	p=0.000 **

Table 6: Wilcoxon-test on the difference between the Markowitz and the behavioral models

The results only show small differences between model M1 and M2 and for different parameters. Even with model M2(0), which completely ignores the expected returns, we get nearly the same effects. This is probably due to the fact that expected returns and volatilities are highly correlated in our data. The mean correlation between the advisors' perceived expected returns and their perceived volatilities is 88.1%. Hence, the financial consultants expect more return from riskier assets. Therefore, it is difficult to distinguish between the two target variables Expected Return and Pure Risk in our models and it is hard to derive any results regarding the best parameters. Nevertheless we find clear evidence for our behavioral hypotheses: Even financial advisors seem to use strategies of naive diversification without considering correlations between asset classes.

Alternative Approaches

Next, we will try to confirm the results of the last section by presenting and discussing some alternative evaluations of our data. One objection might be that investment consultants use the proposed asset allocations of their banks, although we asked them to give their own individual opinions and not the opinion of their banks. Consequently, there might be a discrepancy between their own (biased[36]) market expectations and the bank's recommended asset allocations that drives the deviations from the rational Markowitz model. By using the historical data[37] (see appendix E) instead of the individual market expectations we controlled for this effect in an additional analysis. With these data, the differences between the models get smaller, but we still find significantly better results with the behavioral models (see Table 7). It is only the low-risk-portfolio that cannot be explained any better by the behavioral diversification model. For the average distance measures of all portfolios we still find significantly better results with models M1 and M2.

		M1(0.5)	**M2(0)**	**M2(0.5)**
average distances over all portfolios	opt1	p=0.005 **	p=0.004 **	p=0.004 **
	opt2	p=0.004 **	p=0.004 **	p=0.002 **

Table 7: Wilcoxon-test on the model differences using historical market data

Another objection might be the ways, in which the optimal Markowitz portfolio on the efficient line is determined. So far, we have chosen two ways of determining this portfolio: One by keeping the expected returns constant (model opt2) and one by keeping the volatility of the

[36] As in Siebenmorgen, E.U. Weber and Weber (2000) we find some strong biases especially in the risk perception data regarding volatility of bonds (see appendix E).

[37] We changed the historical mean returns of the asset types "short-term" and "bonds" by using the short-term/long-term interest rates of December 1999 (3% for short-term investments and 5% for long-term investments in bonds). We did that to correct for the relatively low interest rates during our study.

portfolio constant (model opt1), and we received similar results. Alternatively, we now use the following optimization:

<u>"Nearest" Markowitz solution:</u>

$$\underset{\hat{\alpha}_{i,k}}{\mathrm{Min}}\ DM_k\left(\alpha_{i,k}, \hat{\alpha}_{i,k}\right)$$

s.t. There is a $\hat{r}$, for that ($\hat{\alpha}_{i,k}$) is the solution of the following problem:

$$\underset{\tilde{\alpha}_i}{\mathrm{Max}} \sum_{i=1}^{n} \tilde{\alpha}_i \cdot \mu_{i,k}$$

s.t. $$\text{Risk}=\sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n} \tilde{\alpha}_i \cdot \tilde{\alpha}_j \cdot \sigma_{i,k} \cdot \sigma_{j,k} \cdot \rho_{ij,k}} \le \hat{r}$$

$$\sum_{i=1}^{n} \tilde{\alpha}_i = 1 \quad \text{and} \quad 0 \le \tilde{\alpha}_i \le 1 \,\forall\, i = 1,..,n$$

Thus, we allow for the best (i.e., "nearest" to $\alpha_{i,k}$) non-dominated (notice the "≤" in the restriction) solution on the whole efficient frontier (see Figure 10).

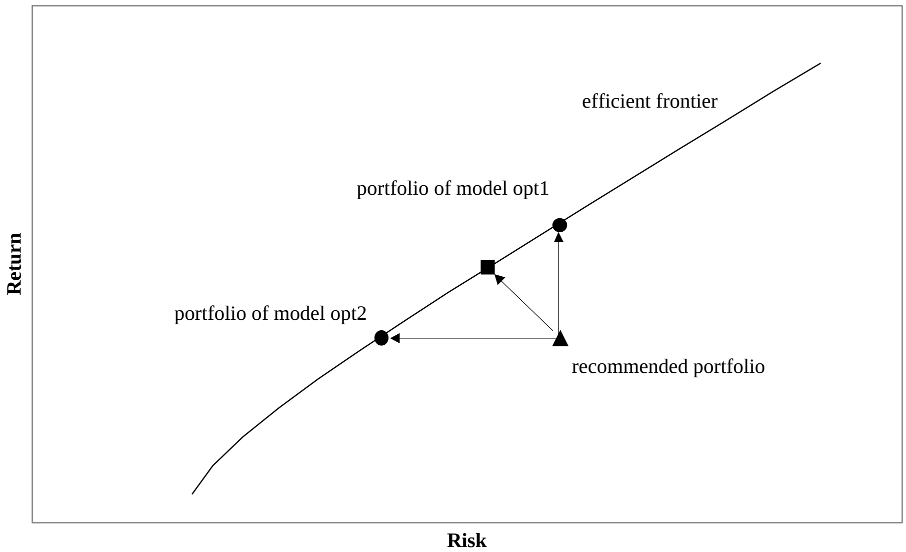


Figure 10: Alternative construction of the benchmark portfolios

Analogously, we define the nearest non-dominated solutions of models M1 and M2 (which coincide with the nearest solutions of models M1b and M2b, respectively). Hence, we determine the model portfolios on the efficient line that have the lowest distance to the recommended portfolio.

For the Markowitz model we find some improvements compared to opt1 and opt2. On the other hand, we do not find any improvements of the behavioral models using this method, probably because of the restriction to efficient portfolios. Nevertheless, the differences are still significant as Table 8 shows[38].

		nearest M1(0.5) solution	**nearest M2(0) solution**	**nearest M2(0.5) solution**
average distances over all portfolios	nearest Markowitz solution	p=0.026 *	p=0.011 *	p=0.008 **

Table 8: Wilcoxon-test on the model differences using the nearest solutions

We think, however, that this is not an appropriate way of modeling portfolio recommendations of investment experts, because very often (12 recommendations) we derive Markowitz portfolios that are substantially different from what has been recommended: For many of these portfolios, risk and also the proportion of stocks differed extremely from those of the recommended portfolios. So we think that it rather disproves the descriptive validity of the Markowitz model when the nearest portfolio on the efficient line tends to be a portfolio with totally different characteristics. For 7 questionnaires it was even the case that the best fitting Markowitz models (using this method) changed their risk order[39]. Obviously, this again indicates that the consultants did not want to recommend these “nearest Markowitz solutions”. On the other hand, the solutions of the behavioral models hardly changed.

[38] This method is particularly interesting, since we have seen in section 3 that certain parameters may lead to dominated solutions in the behavioral models. With this method we exclude dominated solutions. Nevertheless, we find that the behavioral approaches are still significantly better.

[39] E.g. the aggressive benchmark portfolio had less risk than the moderate benchmark portfolio.

Finally, we consider an investor with several bank accounts who talks with more than one expert about his investment intentions. Alternatively, he reads some financial journals with asset allocation recommendations as they are presented in CMW. Finally, he will decide about his money by averaging several portfolio recommendations while his market expectations will be something like the mean market expectations of many bank consultants and financial institutions. For this particular case, the behavioral models (average distance measure for M1(0.5)=13.0%, M2(0)=13.0%, M2(0.5)=12.7%) seem to be 2.5 times better than the Markowitz model (average distance measure opt1=31.9%, opt2=33.9%). Figure 11 shows the mean recommendations for the three clients with different risk attitudes and the results of models opt1 and M2(0.5). Looking at aggregated market expectations and comparing it to the mean portfolio recommendation even strengthens the case of the behavioral model[40].

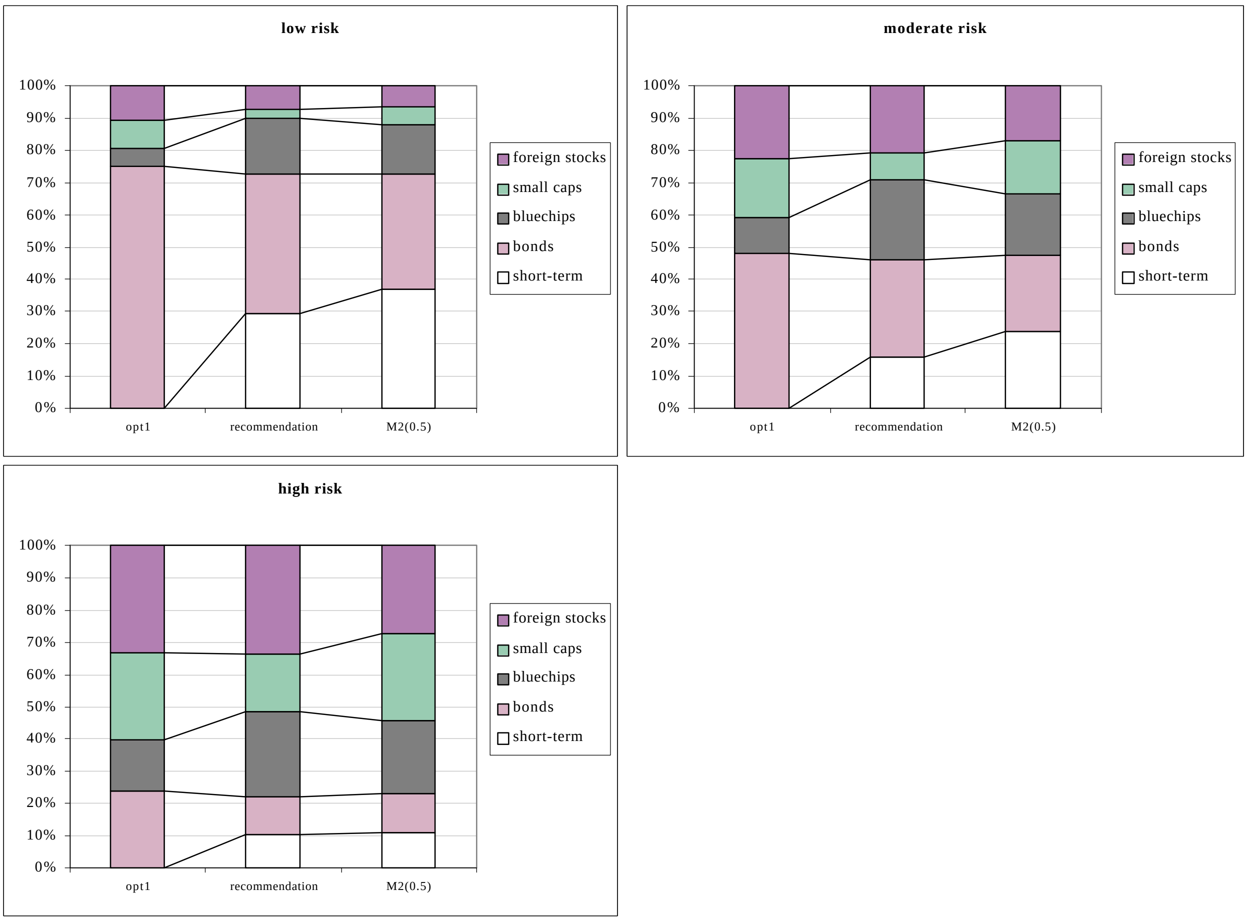


Figure 11: Average portfolio proportions

[40] Even if we assume the volatility of the short-term investment to be 0% (existence of a riskless asset), the Markowitz approach produces 0%-proportions of the short-term investment because of the short-sale constraint.

4.3 Efficiency Losses

CMW and Fisher and Statman (1997b) find that investors' intuitive behavior produces portfolios that are situated surprisingly close to the efficient frontier. Figure 12 is based on the data presented in CMW. The dots show the recommended portfolios while the thin line illustrates the efficient Markowitz frontier in the Standard Deviation-Expected Return diagram. The thick line shows the result of the behavioral model M2(0.5).

It is important to remember that the efficient frontier of the Markowitz model depends on the correlations between the asset returns. The behavioral approach based on pure risk and naive diversification does not. Hence, the efficiency losses will strongly depend on the correlations: The efficiency losses will increase if the investment alternatives offer substantial hedging possibilities (large negative correlations between two assets), because the behavioral model does not take these hedging possibilities into account.

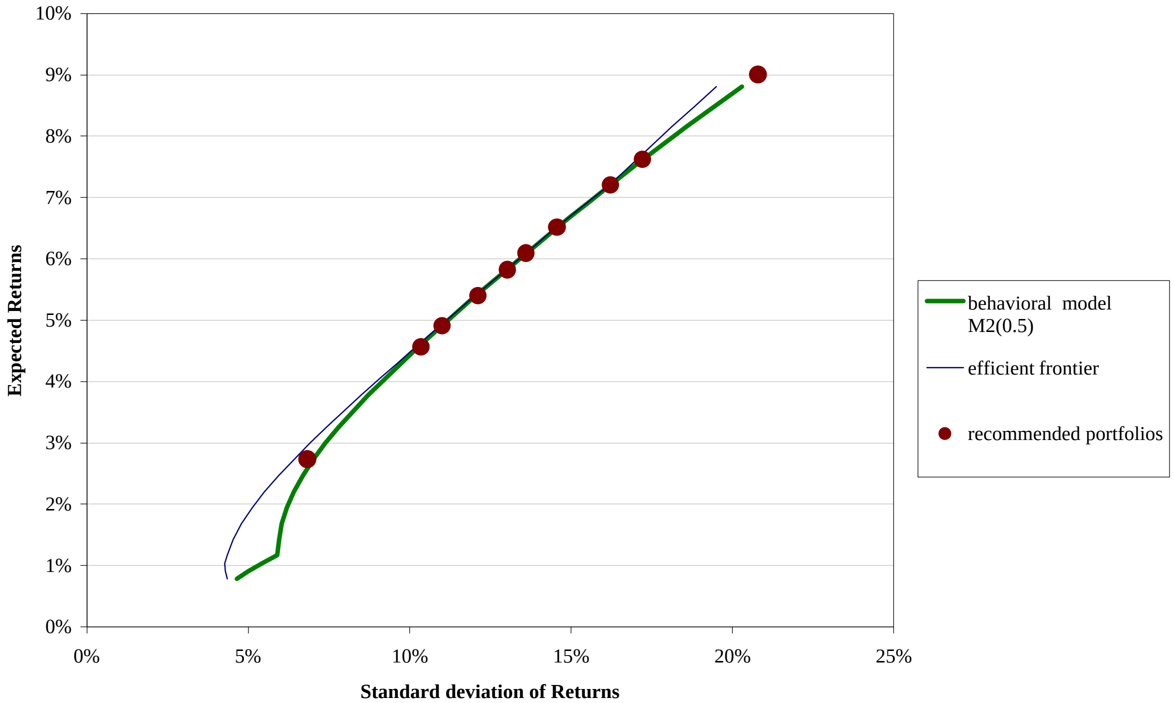


Figure 12: Efficiency losses in CMW

Based on the market expectations of German financial advisors, we find considerable losses in efficiency. Table 9 shows the average losses in expected return per year for each of the three portfolio types. Given their own market assessments, the advisors' portfolio recommendations have expected returns of about 1.5% below the optimal portfolios they could have chosen. This confirms that even (highly trained and highly paid) professional investment advisors do not recommend efficient portfolios. Their tendency to ignore correlations and to diversify naively would cost our fictive investors of $ 250,000 between $ 3,700 (1.48%) and $ 4,175 (1.67%) per year. As Table 9 shows, these average efficiency losses are much lower if we take the historical data to evaluate the recommendations. Given these market parameters a client would lose between $ 600 (0.24%) and $ 1.600 (0.64%) per year.

	low risk	**moderate risk**	**high risk**
individual market expectations	1.56%	1.48%	1.67%
Historical market data	0.39%	0.24%	0.64%

Table 9: Average losses of expected return

5 Conclusion

We have examined the explanatory power of a new behavioral approach to portfolio selection based on the ideas of pure risk and naive diversification. By describing two simple investment models we have been able to explain what is called the asset allocation puzzle pretty well. We tested the model on data presented in literature as well as new data. We asked German financial advisors, i.e. bank employees who are experienced in the field of investment consulting, to answer questions regarding both, investment advice for three fictive clients with different risk attitudes and their market expectations. With these sets of data we could compare the traditional Markowitz approach with the new behavioral approach.

Our first hypothesis is that even experienced investment advisors are not able to consider correlations correctly although they are able to estimate these correlations quite well. This hypothesis has been confirmed. Furthermore, we find that the behavioral model fits the given portfolio recommendations significantly better than the Markowitz model does. We double-check our results with some alternative methods like using historical data and limited risk/return restrictions. Finally, we examine efficiency losses of the recommended portfolios where we find contrasting results. If we use the individual market expectations, efficiency losses tend to be quite substantial, but if we use the historical data, efficiency losses are rather small, as Canner, Mankiw and Weil (1997) and Fisher and Statman (1997a and 1997b) have already found.

It is not clear, which market expectations are really relevant for the investment consultants when they recommend portfolios. Do they use asset allocations of their bank, which are primarily based on historical evaluations or are their recommendations driven by their own market expectations? One way or another – the mechanism that drives the portfolio recommendations seems to differ from normative theory.

Regarding the parameters β and γ of models M1 and M2, we find that the results are robust if the diversification variable has enough weight in the target function. The expected return of the portfolio, however, does not seem to be as important for our results as the low distance measures for model M2(0) reveal. We suspect that this is due to the fact that perceived volatilities and perceived expected returns of the five asset classes tend to be correlated. Therefore the consideration of the expected returns in our models is not as important as the consideration of the diversification term.

It will be interesting to learn more about our proposed models in further studies. Especially the role of the parameters β and γ could be reviewed. What about the models that propose dominated portfolios as solutions? Are these models worse than models that have monotonous efficient frontiers? Is it possible to identify a person-specific parameter? How are β and γ influenced by the number of assets (n) and by the (historical or perceived) market data? Is the model also appropriate for investment problems with much more investment alternatives. In such situations investors and advisors try to “pick” those stocks that seem to be very profitable to them. Then the parameters β and γ will probably influence the trade-off between tendencies towards diversification and tendencies towards stock picking. Does our model capture this situation as well? These are questions that should be examined in further experiments or with real portfolio data. It would be especially important to consider assets whose expected returns and volatilties are less correlated (e.g. in an experiment) to be able to separate the influence of these two target variables.

Finally, it will be an interesting field of future research to investigate whether investors' allocation behavior depends on correlations (which might be the perceived or the historical ones) when the induced efficiency losses are higher. As very negative correlations between two assets offer considerable hedging possibilities, which are not captured by the behavioral models, it might be the case that such low correlations influence portfolio allocations.

Appendix

A. Questionnaire (page 1)

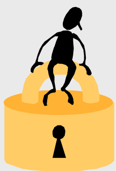
Asset Allocation Questionnaire

We, the Behavioral Finance Group at the University of Mannheim (http://www.behavioral-finance.de), examine the advice of investment consultants. In this context we are especially interested in your recommendations for asset allocations given the momentary market situation. Your advice surely depends on your clients' characteristics, so we ask you to imagine the following scenario.

Three new clients introduce themselves. They have nearly the same characteristics:

Volker Vorsicht, Marcel Moderat and Niko Nervenstark have recently passed their MBA-diploma at the university of Mannheim with good marks. They are 26 years old, single and do not own any real estates or other wealth. Shortly, however, each of them will inherit DM 500,000 from their deceased grandmother. As all of them have accepted their first job offer a few weeks ago (net income: DM 40,000) they have not enough time to invest their new wealth. Asked for their investment goals all of them say that they do not know, when they need the money. Perhaps part of the money in one year for a new car or in five years for a house. Their knowledge about different types of investments is rather good, as they attended the course „Finance" where they even studied derivatives. The three graduates however have different **risk attitudes** as the following statements show.

Volker Vorsicht:



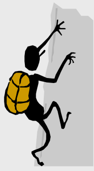
I am cautious. As a MBA-graduate I know that risky assets should have higher returns, but I cannot bear to "gamble" with my grandma's savings. Definitely I am willing to invest part of the capital in stocks and I am willing to accept a possible loss of – let's say – 10% in a year. But after 10 years there should at least remain the DM 500,000 and some interest.

Marcel Moderat:

Please offer me a well-balanced investment strategy, how to invest these DM 500,000. The strategy should have potentials for growth and gains without being too risky. As a result I am completely aware that a possible drawback at the markets might produce a portfolio performance of -20% in one year, which is hard to make up for. That's OK. But please take care that the portfolio risk is not too big.

B. Questionnaire (page 2)

Niko Nervenstark:



As I have never dreamed of these DM 500,000, I do not mind possible losses! I ask you to invest this money in a way, that it will seize very good opportunities for potential gains. Of course I do not want to gamble with this money, but I am willing to accept the high risk of an aggressive and opportunity-taking investment strategy, that makes sense momentarily. So I hope to generate a high income with this heritage.

The following investment alternatives are available:

- „short-term“: interest-paying investments with short duration (in DM or Euro): money market funds, cash accounts, short-term bonds (time to maturity <u>up to 1 year</u>), etc.
- „bonds“: interest-paying investments with longer duration (in DM or Euro): high-quality bonds (time to maturity <u>5 to 20 years</u>), long-term zerobonds or corresponding bond-funds
- „Blue Chips“ German stocks, which belong to the German stock index DAX or mutual funds investing in these stocks
- „Small Caps“ other German stocks, that do not belong to the DAX or corresponding mutual funds
- „Foreign stocks“ a mixture of foreign Blue Chips, Small Caps and mutual funds of foreign stocks, as you prefer it momentarily

Which portfolio allocation do you advise the three guys for the next 12 months. Please insert percentages.

	Volker Vorsicht	**Marcel Moderat**	**Niko Nervenstark**
			
short-term			
bonds			
Blue Chips			
Small Caps			
Foreign stocks			
Sum	**100 %**	**100 %**	**100 %**

Please make sure, that your portfolio proportions add up to 100%.

C. Questionnaire (page 3)

Your Market Expectations.

How do you assess the performances of the mentioned investment alternatives and your portfolio propositions in the next 12 months? Please consider all interest payments, gains/losses (also of bonds because of the interest rate risk), dividend payments and if necessary exchange rate risks.

Please state the **performance** (in %), of which you think the real performance in 12 months will ...

lower bound:	... rather not (i.e. in only **10 %** of all cases) remain under it.
median:	... equally likely exeed it or remain under it.
upper bound:	... rather not (i.e. in only **10 %** of all cases) exeed it.

		lower bound	**median**	**upper bound**
investment alternatives	short-term			
	bonds			
	Blue Chips			
	Small Caps			
	Foreign stocks			
portfolios	V. Vorsicht 			
	M. Moderat 			
	N. Nervenstark 			

Finally we ask you for your opinion to what extent the performances of the five mentioned investment alternatives cohere (statistically spoken: „correlate“). Please mark your expectations with a cross on the scales.

-100%	completely opposite performance processes
± 0%	no coherence
+100%	completely parallel performance processes

coherence **short-term** and **bonds**

% -100 -75 -50 -25 0 +25 +50 +75 +100

coherence **short-term** and **Blue Chips**

% -100 -75 -50 -25 0 +25 +50 +75 +100

coherence **short-term** and **Small Caps**

% -100 -75 -50 -25 0 +25 +50 +75 +100

D. Questionnaire (page 4)

coherence **short-term** and **foreign stocks**

% -100 -75 -50 -25 0 +25 +50 +75 +100

coherence **bonds** and **Blue Chips**

% -100 -75 -50 -25 0 +25 +50 +75 +100

coherence **bonds** and **Small Caps**

% -100 -75 -50 -25 0 +25 +50 +75 +100

coherence **bonds** and **foreign stocks**

% -100 -75 -50 -25 0 +25 +50 +75 +100

coherence **Blue Chips** and **Small Caps**

% -100 -75 -50 -25 0 +25 +50 +75 +100

coherence **Blue Chips** and **foreign stocks**

% -100 -75 -50 -25 0 +25 +50 +75 +100

coherence **Small Caps** and **foreign stocks**

% -100 -75 -50 -25 0 +25 +50 +75 +100

Finally please tell us, which „foreign stocks“ did you have in mind:

Thank you very much for your help. If you give us your email-address, we certainly will inform you about our results. In any case your answers will remain anonymous and will not be linked with your name.

email-address:

For your help you find attached Volume 0 from our series "Research for practitioners".

Behavioral Finance Group
Lehrstuhl für ABWL, Finanzwirtschaft
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E. Market Expectations and Historical data

Expected returns and volatility:

		mean expectation	**historical data[41] (1988-1999)**
short-term	expected return	3.2%	5.7%
	volatility	0.6%	0.7%
bonds	expected return	4.4%	7.1%
	volatility	1.3%	6.8%
blue chips	expected return	12.0%	19.9%
	volatility	8.9%	20.2%
small caps	expected return	14.6%	14.3%
	volatility	12.3%	18.0%
foreign stocks	expected return	15.9%	14.5%
	volatility	12.3%	16.5%

Correlations:

		mean expectation	**historical data (1988-1999)**
short-term	bonds	36.7%	13.8%
short-term	blue chips	-11.3%	-14.1%
short-term	small caps	-16.0%	-8.4%
short-term	foreign stocks	-7.0%	-19.8%
bonds	blue chips	-11.4%	2.0%
bonds	small caps	-9.5%	-8.1%
bonds	foreign stocks	-14.6%	4.2%
blue chips	small caps	50.0%	76.8%
blue chips	foreign stocks	54.1%	63.3%
small caps	foreign stocks	28.4%	49.5%

[41] calculated from the monthly reports of the German central bank "Deutsche Bundesbank" and the indices DAX, SDAX, MSCI-world

F. Portfolio Recommendations

	mean recommended proportion		
	low risk	**moderate risk**	**high risk**
short-term	29.2%	16.0%	10.3%
bonds	43.3%	30.0%	11.9%
blue chips	17.3%	25.1%	26.2%
small caps	2.8%	8.2%	18.1%
foreign stocks	7.3%	20.7%	33.6%

References

Benartzi, S. (1999): Why do Employees Invest Their Retirement Savings in Company Stocks? *Working Paper*, The Anderson School at UCLA.

Benartzi, S./Thaler, R.H. (2000): Naive Diversification Strategies in Retirement Saving Plans. *The American Economic Review*, forthcoming.

Blume, M./Friend, I. (1975): The Asset Structure of Individual Portfolios and Some Implications for Utility Theory. *The Journal of Finance*, 30, 585-603.

Brennan, M.J./Xia, Y. (1998): Resolution of a Financial Puzzle. *Working Paper*, University of California, Los Angeles.

Canner, N./Mankiw, N.G./Weil, D.N. (1997): An Asset Allocation Puzzle. *The American Economic Review*, 87, 181-191.

Clemen, R.T./Fischer, G.W./Winkler, R.L. (2000): Assessing Dependences: Some Experimental Results. *Management Science*, in print.

Clemen, R.T./Reilly, T. (1999): Correlations and Copulas for Decision and Risk Analysis. *Management Science*, 45, 208-224.

Degeorge, F./Jenter, D./Moel, A./Tufano, P. (1999): Selling Shares to Worker-Investors: Analyzing the ‚Ouverture du Capital' at France Télécom. *Working Paper*, HEC School of Management, Jouy en Josas, France.

Elton, E.J./Gruber, M.J. (2000): The Rationality of Asset Allocation Recommendations. *Journal of Financial and Quantitative Analysis*, 35, 27-41.

Fisher, K.L./Statman, M. (1997a): The Mean-Variance-Optimization Puzzle: Security Portfolios and Food Portfolios. *Financial Analysts Journal*, 53, 41-50.

Fisher, K.L./Statman, M. (1997b): Investment Advice from Mutual Fund Companies – Closer to the Talmud than to Markowitz. *The Journal of Portfolio Management*, 53, 9-25.

Joos, C.M./Kilka, M. (1999): Sind Aktienportfolios privater Anleger ausreichend diversifiziert? *Die Bank*, 12/99, 862-866.

Keefer, D.L./Bodily, S.E. (1983): Three-point Approximations for Continuous Random Variables. *Management Science*, 29, 595-609.

Kelly, M. (1994): All their Eggs in One Basket: Portfolio Diversification of US Households. *Journal of Economic Behavior and Organization*, 27, 87-96.

Kroll, Y./Levy, H. (1992): Further Tests of the Separation Theorem and the Capital Asset Pricing Model. *The American Economic Review*, 82, 664-670.

Kroll, Y./Levy, H./Rapoport, A. (1988a): Experimental Tests of the Mean-Variance Model for Portfolio Selection. *Organizational Behavior and Human Decision Processes*, 42, 388-410.

Kroll, Y./Levy, H./Rapoport, A. (1988b): Experimental Tests of the Separation Theorem and the Capital Asset Pricing Model. *The American Economic Review*, 78, 500-519.

Lintner, J. (1965): Security Prices, Risk, and Maximal Gains from Diversification. *The Journal of Finance*, 20, 587-615.

Markowitz, H.M. (1952): Portfolio Selection. *The Journal of Finance*, 7, 77-91.

Mossin, J. (1966): Equilibrium in a Capital Asset Market. *Econometrica*, 34, 768-783.

Oehler, Andreas (1995): Die Erklärung des Verhaltens privater Anleger. *Schaeffer-Poeschel*, Stuttgart.

Read, D./Loewenstein, G. (1995): Diversification Bias: Explaining the Discrepancy in Variety Seeking between Combined and Separated Choices. *Journal of Experimental Psychology: Applied*, 1, 34-49.

Schröder-Wildberg, U. (1998): Entscheidungs- und Lernverhalten an Wertpapiermärkten: Psychologische Aspekte von Börsenentscheidungen. *Gabler/DUV*, Wiesbaden.

Sharpe, W.F. (1964): Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk. *The Journal of Finance*, 19, 425-442.

Shefrin, H./Statman, M. (2000): Behavioral Portfolio Theory. *Journal of Financial and Quantitative Analysis*, 35, 127-151.

Siebenmorgen, N./Weber, E.U./Weber, M. (2000): Communicating Asset Risk: How the format of historic volatility information affects risk perception and investment decisions. *Working Paper 00-38*, Sonderforschungsbereich 504, Universität Mannheim.

Thaler, R.H. (1985): Mental Accounting and Consumer Choice. *Marketing Science*, 4, 199-214.

Weber, E.U. (2000): Decision and Choice: Risk, Empirical Studies. To appear in: International Encyclopedia of the Social & Behavioral Sciences, *Elsevier Science*, Amsterdam et al.

Weber, M. (2000): Decision and Choice: Risk, Theories. To appear in: International Encyclopedia of the Social & Behavioral Sciences, *Elsevier Science*, Amsterdam et al.

Weber, M./Camerer, C. (1998): The Disposition Effect in Securities Trading: An Experimental Analysis. *Journal of Economic Behavior & Organization*, 33, 167-184.

Nr.	Author	Title
00-49	Thomas Langer Martin Weber	The Impact of Feedback Frequency on Risk Taking: How general is the Phenomenon?
00-48	Niklas Siebenmorgen Martin Weber	The Influence of Different Investment Horizons on Risk Behavior
00-47	Roman Inderst Christian Laux	Incentives in Internal Capital Markets
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