Employment Risk and Compensation Incentives as Determinants of Managerial Risk Taking*

- Evidence from the Mutual Fund Industry -

Alexander Kempf
kempf@wiso.uni-koeln.de
www.wiso.uni-koeln.de/finanzierung

Stefan Ruenzi
ruenzi@wiso.uni-koeln.de
www.wiso.uni-koeln.de/finanzierung

Tanja Thiele
tanja.thiele@gmx.de
www.wiso.uni-koeln.de/graduiertenkolleg

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Kempf and Ruenzi are at the Department of Finance, University of Cologne, Albertus-Magnus Platz, 50923 Koeln, Germany. Thiele is at the Graduate School of Risk Management at the University of Cologne, Albertus Magnus Platz, 50923 Koeln, Germany. All authors are members of the Centre for Financial Research (CFR) Cologne. Thiele gratefully acknowledges financial support from the German Research Foundation (DGF). We thank participants at the CFR Cologne/Tübingen joint graduate seminar for helpful comments and suggestions.

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- Evidence from the Mutual Fund Industry -

Abstract

We examine the influence of employment risk and compensation incentives on managerial risk taking. Our empirical investigation of the risk taking behaviour of equity fund managers during 1980 to 2003 shows that these incentives crucially depend on the probability and likely costs of job loss. Aggregate stock market returns are a proxy for this: in bull markets, the probability of job loss is low for fund managers and compensation incentives dominate. In contrast, in bear markets it is more likely that fund managers loose their job and at the same time there are not many new jobs available. Consequently, employment incentives dominate in bear markets. This leads to diametrical risk adjustment strategies. In bull markets, midyear losers increase fund risk more than midyear winners, and vice versa in bear markets.

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1. Introduction

In this paper we empirically examine risk taking behaviour of fund managers. In making their investment decisions, fund managers face two main incentives. On the one hand, they want to reach a top performance in order to gain large inflows of new money and eventually a high compensation. We term these incentives 'compensation incentives'. On the other hand, they do not want to loose their job in order to prevent the likely costs associated with being laid-off. We term these incentives 'employment incentives'. We analyze how compensation and employment incentives interact in determining the risk taking behavior of fund managers.

Brown/Harlow/Starks (1996) analyse the compensation incentives fund managers face. They show that managers compete against each other in a tournament. Their results suggest that fund managers adjust the risk of their portfolio dependent on their midyear performance in order to reach a top position by the end of the year. They do so in order to maximize expected future inflows, which positively depend on performance (Sirri/Tufano (1998)). We argue that employment incentives also lead fund managers to adjust their risk dependent on their midyear performance. However, we expect that compensation and employment incentives are diametrical: while compensation incentives lead fund managers whose performance lags behind after the first part of the year (midyear losers) to increase their risk more than midyear winners, employment incentives lead midyear losers to decrease their risk.

Ex ante, it is not clear whether compensation incentives or employment incentives are dominant. However, our following analysis shows that the relative strength of these two incentives depends on the market phase. Specifically, compensation incentives dominate in bull markets, because here potential gains from achieving a top position are largest. In contrast, employment incentives dominate in bear markets, because here employment risk is highest. Thus, we can formulate the following testable hypothesis: (1) Losers increase risk more than winners in bull markets. (2) Losers decrease risk more than winners in bear markets. To our best knowledge, this paper is the first to study the fund managers' incentives and eventually risk taking dependent on market phases.

We use portfolio holdings data of US equity mutual funds over the period 1980 to 2003 to test our hypotheses. Our results support our hypothesis. In bear markets, employment incentives dominate and losers increase risk less than winners do. In bull markets, compensation incentives are stronger and losers increase risk more than winners do. These findings suggest that the market phase is a crucial determinant of risk taking behaviour. Surprisingly, the influence of bull and bear markets has been completely ignored in studies of fund manager's risk taking behaviour so far. Our results indicate that neglecting the influence of the market phase can easily yield misleading results.

Analyzing the risk taking behaviour of fund managers using portfolio holdings allows us to examine the fund manager's intended rather than the realized change in risk between the first and the second half of the year. This is a more exact measure of the fund manager's reaction to the incentives she faces than the realized change in risk. Looking at realized changes in risk does not allow us to distinguish between intended changes in risk and unexpected changes in risk due to changes in the risk of the stocks in the portfolio.

Using holdings data also allows us to examine fund managers' response to risk surprises, i.e. to the unexpected proportion of fund risk in the first half of the year. We document a strong influence of the risk surprise on the change in risk between the first and the second half of the year. If realized risk exceeds intended risk, managers try to decrease their risk-level, and vice versa. This is consistent with the idea that fund managers are constrained by risk-limits (see, Daniel/Wermers (2000)) and suggests that fund managers' risk adjustments are driven by the desire to meet these constraints rather than by changing expectations concerning risk premia.

In the following section, we analyze the impact of compensation and employment incentives on managerial risk taking as well as the influence of the market phase and derive our hypothesis. There, we also relate our study to the literature. Section 3 introduces the data and details, how the intended risk taking of fund managers can be calculated. In Section 4, we empirically examine the influence of compensation and employment incentives on managerial risk taking. Section 5 offers some robustness tests and Section 6 concludes.

2. Compensation Incentives and Employment Incentives in Bull and Bear Markets – Intuition and Testable Implications

2.1 Impact of Compensation Incentives and Employment Incentives on Risk Taking

There is extant empirical evidence, that the relationship between net-flows of new money into a mutual fund and its past performance is positive and convex (see, e.g., Sirri/Tufano (1998), Chevalier/Ellison (1997), and Fant/O'Neal (2000)). Top-performers get the lion's share of new money inflows, while net-flows of funds with a mediocre and a bad past performance hardly differ. As a fund manager's compensation depends on her assets under management (Khorana (1996)), she will try to reach a top position in order to increase her income. Brown/Harlow/Starks (1996) argue that the convex performance flow relationship leads to risk taking incentives that are comparable to a tournament. They show that managers with a bad midyear performance (losers) try to catch up with those funds with a good midyear performance (winners) by increasing their risk. While the option-like convex performance flow relationship generally leads to incentives to increase risk for all managers, incentives to do so are higher for losers than for winners. The reason is that losers have nothing to lose from a further deterioration of their position in terms of inflows and eventually income. However, increasing risk increases their chance of catching up with the winners. In contrast, winners have incentives to play it safe and lock in their leading position. For them, increasing their risk also increases the risk of losing their winning position. Thus, midyear losers increase risk more than midyear winners due to these compensation incentives.

However, managers not only care about reaching a top position. They are also concerned about not loosing their job. For a manager, such employment incentives are of concern because loosing her job entails significant costs in terms of foregone income, loss in reputation and the loss of future job opportunities. The probability of forced turnover is much higher for fund managers with poor past performance. Khorana (1996), Chevalier/Ellision (1999), and Hu/Hall/Harvery (2000) find a negative relationship between the probability of (forced) managerial turnover and past performance of fund managers.[1] Thus, employment risk is a major concern for fund managers whose midyear performance is relatively bad, as the probability of loosing their job is already high for them. Bloom/Milkovich (1998) show that an increase in the risk of investment projects also increases the probability of a bad performance outcome, which might trigger job loss. Thus, employment incentives cause midyear losers to decrease their risk.[2] For midyear winners, the probability of losing their job due to a bad performance is small. For them, employment incentives are of little or no relevance. Thus, the thread of dismissal leads to stronger incentives for losers to decrease their risk than for winners.

Overall, our analysis shows that employment incentives and compensation incentives work in the opposite direction of each other. We now discuss under which circumstances one or the other can be expected to dominate.

2.2 Influence of Bull and Bear Markets on the Relative Strength of Incentives

We argue that the strength of employment incentives and compensation incentives depends on the market phase, i.e. if the market is bullish or bearish. Warther (1995) documents that aggregate inflows into funds are generally lower after bear markets than after bull markets. Thus, compensation incentives to reach a top position are weaker in bear markets than in bull markets, because the flows that can be captured by reaching a top position are relatively low in this case. Furthermore, the overall number of funds usually decreases after bear markets. This is also due to lower inflows, which eventually leads to more fund closures (Zhao (2005)). Consequently, the thread that the fund manager's fund will be closed and she looses her job is more severe in bear than in bull markets. At the

[1] There is a large body of empirical research showing a negative relationship between performance and termination risk for industrial companies (Coughan et al. (1985), Gilson (1989), Murphy/Zimmermann (1993)).

[2] For fund managers with extremely bad performance after the first half of the year, there might also be an incentive to 'gamble for resurrection' (see Hu/Kale/Subramaniam (2005)). However, the 'gamble for resurrection' argument only is strong if fund managers are myopic, i.e. if they do not take into account their chance of finding a new job after being laid-off. If they are not myopic, they are less inclined to gamble for resurrection, because this increases the likelihood of a really catastrophic performance (entailing a complete destruction of the manager's reputation) and eventually of never finding a new job in the industry again. In order not to complicate the analysis, we abstract from this extreme incentive.

same time, fewer new funds are started (Zhao (2002)). Thus, if a fund manager actually loses her job in a bear market, she will also have more trouble finding a new job in the fund industry than in a bull market, because the number of available positions will be low. Following this line of reasoning, employment incentives are very strong in bear markets, while compensation incentives are relatively weak.

In contrast, following bull markets, there are only very few fund closures and a lot of new fund openings (Zhao (2002)). Thus, fund managers are less likely to loose their job in the first place and are also more likely to find a new job even if they should still be laid-off. In this case, fund managers are a scarce resource and the thread of dismissal is not severe. Furthermore, aggregate flows into the market are much higher in bull markets than in bear markets (Warther (1995)). As mainly the best funds profit from these inflows, fund managers have strong incentives to reach a top position. Consequently, compensation incentives are very strong in this case, while employment incentives are relatively weak.

From this analysis, we conclude that compensation incentives dominate in bull markets, while employment incentives dominate in bear markets. Thus, we formulate the following testable hypotheses: In bull markets, midyear losers increase their risk more than midyear winners. In bear markets, midyear losers decrease their risk more than midyear winners. These hypotheses are tested in Section 4.

2.3 Related Literature

Our study is most closely related to the extant empirical work on tournament incentives in the fund industry. This literature starts with the influential study of Brown/Harlow/Starks (1996). They document that midyear losers increase risk more than midyear winners. This finding is confirmed in several follow-up studies like Koski/Pontiff (1999), Qiu (2003), and Elton/Gruber/Blake (2003). However, more recent studies have questioned this finding. Busse (2001) finds that losers increase risk less than winners do. While most studies use monthly returns to examine risk taking, he uses daily return data and attributes his diverging finding to data frequency.[3] Kempf/Ruenzi (2002) and Jans/Otten (2006) report, that the risk taking behaviour of fund managers is not stable over time.

There is only very little empirical evidence on the influence of employment risk on managerial risk taking behaviour. One notable exception is Chakraborty/Sheikh/Subramanian (2006) who find that managers of industrial firms who face a high termination risk make less risky decision than managers with a low probability of losing their job. Chevalier/Ellison (1999) examine career concerns of fund managers. They argue that 'the desire to avoid termination is the most important career concern' (p. 426). They find that younger managers face a higher employment risk and eventually tend to herd more towards conventional investment styles and take less (idiosyncratic) risk than older manager, whose employment risk is lower. However, they do not examine the interplay between employment incentives and compensation incentives.

We are aware of no other studies that examine the impact of the market phase on managerial incentives. The reaction of managers in response to risk surprises is also not analyzed in the literature so far. For industrial firms, the reason for this might be that it is difficult to come up with a measure of unintended risk realizations for these firms. Looking at studies that examine mutual fund managers, most authors analyze risk based on realized returns of funds. This does not allow them to differentiate between intended and realized risk and eventually calculate risk surprises. Nevertheless, Daniel/Wermers (2001) analyze the impact of realized risk in the first half of the year on fund managers' risk adjustment and find that it has a negative impact. They argue that this could hint at some kind of risk budgets fund manager are constrained by. However, Koski/Pontiff (1999) argue that a negative relationship could also be due to measurement problems causing mean reversion in fund volatility. This study is the first attempt to explicitly examine reactions of managers to unintended risk realization.

[3] However, Goriaev/Nijman/Werker (2005) argue that daily data should not be used for tests of fund managers' tournament behavior. They show that tests using monthly data are more robust than test using daily data.

3. Methodology

3.1 Data

Our analysis is based on three comprehensive databases. The data we examine is created by merging the Center for Research in Security Prices (CRSP) U.S. Stock database with the Thomson Financial Mutual Fund Holdings database and the CRSP Survivor-Bias Free U.S. Mutual Fund database. The Thomson Financial Mutual Fund Holdings database includes information on all U.S. mutual funds from 1975 on.[4] It comprises the names of the funds, their complete portfolio holdings and their total net assets under management (TNAs). Since June 1980 the date of the portfolio "snapshot" (hereinafter, report date) and self-declared investment objectives are itemised. Portfolio holdings for each fund are stated either quarterly or semi-annually. The data are sourced from reports filed by the funds with the Securities and Exchange Commission (SEC) or from voluntary reports by the funds.[5] The second database is the CRSP Survivor-Bias Free U.S. Mutual Fund database. It includes information on virtually all U.S. open end mutual funds starting in 1962. It comprises the name of the fund, monthly net returns, total net assets under management, investment objectives, and further fund specific information. The CRSP Survivor-Bias Free U.S. Mutual Fund database contains information on each individual share class offered by a fund. The third data source is the CRSP U.S. Stock database. It provides information about U.S. stocks traded at the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX) and the NASDAQ. It includes information on daily stock prices and returns as well as dividends and market capitalisations for all stocks. We merge all three data sources. Details pertaining to the merging procedure are contained in the appendix.

In order to calculate meaningful risk measures for the funds in our sample based on portfolio holdings, we limit our sample to diversified equity funds which invest at least 50% in U.S. equities. This is necessary, because the CRSP U.S. Stock database only includes return information on U.S. stocks. Thus, we only consider funds that belong to the investment objectives "Small Company Growth", "Other

[4] The database was formerly known as CDA/Spectrum.

[5] Until 1985 the SEC required quarterly reports. In 1985 the mandatory portfolio disclosure frequency was reduced from every quarter to every six months. In 2004 the SEC increased the mandatory frequency back to quarterly.

Aggressive Growth“, “Growth“, “Growth and Income“, “Income“, “Maximum Capital Gains” and “Balanced”.[6] We exclude all other funds like international funds, bond funds and index funds. Our final sample includes 18.924 yearly observations of mutual fund data starting in 1980. It ends in 2003. Summary statistics of our sample are presented in Table 1.

- Please insert TABLE 1 approximately here -

The total number of funds increases from 254 in 1980 to 1.710 in 2001. In 2003, there are 1.226 funds in our sample. Similarly, from 1980 to 2000 the mean total net assets per fund rise from 181 to 1.464 million USD and then slightly decrease to 1.164 million USD in 2003. The average age of the funds decreases steadily due to the large number of newly founded funds. The average turnover is slightly higher in the more recent years than in the earlier years.

In order to define market phases as bull- or bear markets, we calculate midyear returns of the whole stock market. The CRSP U.S. Stock database allows us to calculate the midyear return and the return p.a. of the value-weighted index for all securities that are traded at the NYSE, AMEX and NASDAQ (CRSP-Index). We define a year as a bull market, if the midyear return of the CRSP-Index is positive. If the return is negative, the year is defined as a bear market. We use midyear index returns rather than yearly index returns to classify market phases, because fund managers are assumed to adjust their risk between the first and the second half of the year. At this point in time, midyear returns are the only information available to fund managers with respect to the market phase. Using this procedure, we classify the years 1982, 1984, 1992, 1994, 2000, 2001 and 2002 as bear markets and the other years as bull markets. Information on midyear- and yearly index returns are provided in the last two columns of Table 1. In most cases, yearly returns are positive if the market is classified as a bull market based on the midyear returns and vice versa for bear markets. Thus, it appears reasonable to

[6] Although Thomson offers uniform investment objectives for the whole time period, this information is missing in the data for many funds from 1999 on. The CRSP Survivor-Bias Free U.S. Mutual Fund database do not include uniform investment objectives for the whole time period. Hence, we combine different investment objective classifications (OBJ, ICDI and SI_OBJ) from CRSP to form uniform investment objectives. The procedure is similar to the one used by Pastor/Stambaugh (2002).

assume that fund managers use midyear returns as a proxy for yearly returns and eventually the market phase.

3.2 Construction of Realized and Intended Risk Variables

Several recent papers analyze the risk taking behaviour of mutual funds using fund return data (see, e.g., Brown/Harlow/Starks (1996), Koski/Pontiff (1999), Busse (2001), Elton/Gruber/Blake (2003)).[7] They examine the change in realized fund volatility from the first to the second half of the year. In contrast, we use information about the portfolio holdings of mutual funds. This offers two main advantages. Firstly, while most studies relying on return data only use monthly observations to calculate fund risk in the first and second half of the year, we can calculate more exact measures of actual fund risk by combining information on portfolio holdings and individual stock return data. Using holdings data allows us to utilize the associated stock return data and estimate volatility based on 26 weekly observations (instead of only six monthly observations on fund returns).[8] Secondly, using holdings data allows us to calculate the intended change in risk between the first and the second half of the year. This can deviate substantially from actual changes in fund risk because changes in the risk of stocks affect the change of funds' volatility dramatically (see Busse (2001)). However, fund managers neither know about the direction nor about the degree of future changes in stock volatility at the moment they alter their portfolio. We assume that they only use past stock return information to predict the risk of the portfolio holdings that they choose. Thus, we argue that intended risk changes are a better measure of the response of fund managers to the incentives they face than realized risk changes. Furthermore, using holdings data we can also calculate the difference between intended and realized risk for the first half of the year, which allows us to compute risk surprises.

For each fund and year, we compute three risk variables: realized portfolio risk in the first half of the year, $\sigma_{it}^{(1)}$, intended portfolio risk for the second half of the year,

[7] The only exception we are aware of are Chevalier/Ellison (1997), who also use holdings data to examine risk taking of fund managers.

[8] Fund return data are only available on a monthly basis in the CRSP database. The drawback of our approach to calculating portfolio standard deviation is that we are restricted by having only two or four portfolio snapshots per year.

$\sigma_{it}^{(2),\text{int}}$, and the risk surprise in the first half of the year as difference between intended and realized portfolio risk for the first half of the year: $\sigma_{it}^{(1)} - \sigma_{it}^{(1),\text{int}}$. We now detail how we calculate these variables. The information about the portfolio holdings are available quarterly or semi-annually. Hence, we assume the funds to change their holdings only once in the middle between the report dates. To calculate the realized standard deviation of the funds' portfolio in the first half of the year, $\sigma_{it}^{(1)}$, we compute 26 weekly portfolio returns. To this end, we first calculate 26 sets of portfolio weights. We do so by assuming that the number of shares held by the fund for each firm in the portfolio remains constant. Therefore, we use the respective portfolio holdings from the first half of the year and the actual stock prices of every week in the first half of the year to calculate weekly portfolio weights.[9] Secondly, we multiply the generated portfolio weights with the actual stock returns from the respective week. This procedure is visualized in Panel A in Figure 1. Portfolio holdings are adjusted for stock splits. $\sigma_{it}^{(1)}$ is then defined as the time series standard deviation of the weekly returns of this portfolio.

- Please insert FIGURE 1 approximately here -

To compute the intended standard deviation of the funds' portfolio in the second half of the year, $\sigma_{it}^{(2),\text{int}}$, we calculate 26 hypothetical portfolio returns in the following way: first, we calculate portfolio weights from the average portfolio holdings from the second half of the year by using stock prices at the end of June.[10] Then, we multiply the generated portfolio weights with stock returns of each week in the first half of the year.[11] Thereby, we assume that fund managers calculate expected portfolio risk for the second half of the year based on risk

[9] Unlike Chevalier/Ellison (1997) we focus on the whole portfolio rather than only on the equity part. Securities which are not part of the CRSP U.S. Stock database (mostly cash in our sample) are assumed to generate no return. This procedure is used because we want to include changes of volatility caused by changes of cash quotes.

[10] Average portfolio holdings are calculated as time-weighted average of the respective portfolio holdings in the second half of the year.

[11] We deviate from Chevalier/Ellision (1997), who use prior year data, by calculating the realized as well as the intended standard deviations using stock returns from the first half of the respective year. The reason for this is that we want to grasp the realized standard deviation as exact as possible and include as much stocks that only recently came into existence as possible.

realizations in the first half of the year. This gives us a weekly portfolio return time series. $\sigma_{it}^{(2),\text{int}}$ is defined as standard deviation of this portfolio return time series. Panel B in Figure 1 visualizes the calculation of the intended standard deviation in the second half of the year. Defining intended risk allows us to calculate and analyse intended risk changes instead of realized risk changes in our examinations of managerial risk taking. Thereby, unlike studies calculating risk changes by relying on fund return information only, we can focus on changes in risk due to actual portfolio changes. Our methodology allows us to exclude unexpected changes in fund risk that are due to unexpected changes in the risk of the stocks held by the fund.

Using the same method as above, we also compute the intended risk in the first half of the year, $\sigma_{it}^{(1),\text{int}}$. This allows us to calculate unexpected risk realizations by looking at the difference between realized and intended risk. Thus, we can also examine how fund managers react to such surprises.

4. Intended Risk Taking in Bull and Bear Markets

4.1 Subsample Evidence

According to our hypotheses, we expect compensation incentives to dominate in bull markets and employment incentives to dominate in bear markets. As a first simple test of these hypotheses, we relate the midyear performance of a fund to its intended risk change between the first and the second half of the year. We estimated the following model for subsamlpes consisting of observations from bull market years only and bear market years only, respectively:

$$\sigma_{it}^{(2),\text{int}} - \sigma_{it}^{(1)} = a + b \cdot rank_{it}^{(1)} + c \cdot \left(\sigma_{med,t}^{(2),\text{int}} - \sigma_{med,t}^{(1)} \right) + \varepsilon_{it}. \qquad (1)$$

The dependent variable, $\sigma_{it}^{(2),\text{int}} - \sigma_{it}^{(1)}$, is the intended change in fund *i*’s portfolio standard deviation between the first and the second half of year *t*. $\sigma_{it}^{(1)}$ is the realized standard deviation in the first half of the year and $\sigma_{it}^{(2),\text{int}}$ is the intended standard deviation in the second half of the year. The main explanatory variable in

(1) is the rank of fund *i* in the first half of the year *t* as compared to the other funds in the same segment, denoted by $rank_{it}^{(1)}$. It captures the fund's midyear performance. Ranks are calculated for each segment and each year separately. They are based on raw returns and are normalized to be equally distributed between 0 and 1, with the best fund in its respective segment getting assigned the rank number 1. Thus, fund observations from segments of different sizes are directly comparable.[12] Similarly as in Kempf/Ruenzi (2006), we include the segment median of the dependent variable, $\sigma_{med,t}^{(2),\text{int}} - \sigma_{med,t}^{(1)}$, as control variable. In this expression, $\sigma_{med,t}^{(2),\text{int}}$ ($\sigma_{med,t}^{(1)}$), is the median intended (realized) standard deviations in the second (first) half of the year. This variable captures different variations in the risk level of various segments.

If the influence of the rank is positive, this suggests that funds with high ranks (winners) tend to increase their risk more than funds with low rank numbers (losers). We expect compensation incentives to dominate, i.e. losers to increase their risk more than winners, in bull markets (b <0), and employment incentives do dominate, i.e. winners to increase their risk more than losers, in bear markets (b >0).

Panel A of Table 2 summarizes estimation results of Model (1) for the two subsamples of bull and bear markets, respectively. There, we also present estimation results for the full sample. All estimations include time-fixed effects.

- Please insert TABLE 2 approximately here -

In both subsamples the influence of the performance rank is significant at the one percent level. Thus, we can reject the null-hypothesis that the segment rank has no influence of the intended risk taking if we distinguish between bull and bear markets. In the subsample of bull markets the rank coefficient b is significantly negative, whereas in the subsample of bear markets the rank coefficient b is

[12] We use performance ranks based on raw returns rather than the performance itself or the risk-adjusted performance, since fund investors mainly care about return ranks in making their investment decisions (see, e.g., Sirri/Tufano, 1998 and Patel/Zeckhauser/Hendricks, 1994). Consequently, return ranks are the best measure to capture the influence of the incentives fund managers face.

significantly positive. The market phase has a deciding influence on the way fund managers change their risk: in bull markets losers increase their risk more than winners and in bear markets winners increase their risk more than losers. This supports our argument that compensation incentives dominate in bull markets and employment incentives dominate in bear markets.

The magnitude of the effects is economically significant, too. Our estimates indicate that in bear markets, for example, the best fund managers increase their intended standard deviation by 0.016 points more than the worst fund managers. The average realized standard deviation of funds' portfolios in the first half of the year is 0.152 points. Thus, in this case, the best fund managers intend to increase their risk by 10.5 percent more than the worst fund managers.

For reasons of comparability with existing studies, in the last Column of Panel A, we also report estimation results for the whole sample, where observations of bull and bear markets are pooled together. The coefficient on the influence of the rank is virtually zero. It is neither significant in statistical nor in economic terms. Given our findings from above, this is not surprising. Neither market nor employment incentives dominate, because the full sample consists of bull and bear markets. This indicates that not distinguishing between bull- and bear markets in examinations of managerial risk taking can lead to misleading results.

Our findings are also consistent with the results of Brown/Harlow/Starks (1996). They find no difference pertaining to risk taking between winners and losers for the period from 1980 to 1985, but find more risk taking of losers than of winners for the period from 1986 to 1991. This can be explained by the fact that the number of bull and bear markets is roughly equal in the first period (1982 and 1984 are classified as bear markets, the other three as bull markets), while the latter period is dominated by bull markets (all years are classified as bull markets). Thus, for the 1980 to 1985 period, compensation and employment incentives cancel out, while compensation incentives clearly dominate in the period from 1986 to 1991. This can explain the temporal change in behaviour documented in Brown/Harlow/Starks (1996).

The coefficient c for the influence of the median intended risk adjustment in the segment has the expected sign. It is significant positive at the one percent level.

Fund managers are geared up towards the median intended change of risk of all funds in their segment.

4.2 Yearly Regressions

In order to get a more detailed view of the influence of market phases on risk taking we now turn to an examination of yearly subsamples. On the basis of our findings regarding bull and bear markets, we expect time-varying risk taking behaviour with a certain structure here, too. Similarly as above, when running yearly regressions of Model (1), the rank coefficient b should be negative in bull markets, and positive in bear markets. The estimation results of the rank coefficients for yearly regressions of Model (1) are represented in Panel B of Table 2. Despite the large noise entailed in yearly regressions, we still find very clear results. In 19 out of 24 cases, the direction of the influence of the segment rank is as expected. The coefficient is significant in 18 of these cases. There is only one year (1988), in which the coefficient has a wrong sign that is significant. The pattern of diametrical risk taking behaviour in bull and bear markets appears to be remarkably stable over the time.

4.3 Influence of the Strength of the Incentives

Up to this point we only classified years as bullish or bearish. However, if the market shows a very strong upward movement, i.e. is very bullish, compensation incentives might be stronger than if the market is only slightly bullish. The very good performance of the market attracts the investors' attention and their desire to participate in future gains, while moderately positive returns have less such effect. A similar argument can be made with respect to employment incentives and how bearish markets are. Thus, we expect a negative relationship between the midyear return of the market in a given year and the respective estimated rank coefficient for this year as reported in Panel B of Table 2. A graphical illustration of the relationship between both variables is presented in Figure 2. In Panel A, we plot the midyear return of the CRSP-Index as reported in Table 1 against the estimated rank coefficient for the same year. The years are arranged in ascending order according to their market return in the first half of the year. Panel B plots the same relationship for the significant coefficients only.

- Please insert FIGURE 2 approximately here -

The graphical illustrations show a clear negative relationship between the midyear return of the CRSP-Index and the rank coefficient. This suggests that not only the sign, but also the extent is relevant for the level of the rank coefficient. Compensation incentives increase with the extent of the market return, while employment incentives decrease. The more bullish (bearish) markets are, the more fund managers adjust their risk in response to compensation (employment) incentives.

As a more formal test of this relationship, we estimate the following regression:

$$b_t = \alpha + \beta \cdot ret_t^{CRSP-Index} + \varepsilon_t, \tag{2}$$

where we relate the estimated coefficients b_t from yearly estimations of Model (1) (see Panel B of Table 2) to the midyear return of the CRSP-Index, $ret_t^{CRSP-Index}$, for the respective year. Estimation results are presented in Table 3.

- Please insert TABLE 3 approximately here -

The coefficient α is $-0,096$ and $-0,119$, respectively, depending on whether we include all, or just the significant rank coefficients. In either case, the coefficient is significant at the one percent level. The more extreme the return of the CRSP-Index is, the more pronounced is the impact of the return rank on risk taking. This indicates that the strength of compensation incentives and employment incentives not only depends on whether the market is bullish or bearish, but also upon how bullish or bearish, respectively, the market is.

4.4 Dummy Interaction and Temporal Stability

Instead of using subsamples, we alternatively use a dummy approach to analyse the influence of bull and bear markets on the relationship between the relative midyear performance and the intended change in risk between the first and second half of the year. Interacting the influence of the rank from Model (1) with dummy variables that indicates whether the market is bullish or bearish allows us to examine all years in one pooled regression:

$$\sigma_{it}^{(2),\mathrm{int}} - \sigma_{it}^{(1)} = a + b^{bull} \cdot rank_{it}^{(1)} \cdot D_t^{bull} + b^{bear} \cdot rank_{it}^{(1)} \cdot D_t^{bear} + c \cdot \left(\sigma_{med,t}^{(2),\mathrm{int}} - \sigma_{med,t}^{(1)} \right) + \varepsilon_{it}. \qquad (3)$$

D_t^{bull} (D_t^{bear}) is a dummy variable which is equal to one, if the CRSP-Index is positive (non-positive) in the first half of year *t*, and zero otherwise. The other variables are defined as above. According to our hypothesis, we expect losers to increase their risk more than winners in bull markets ($b^{bull}<0$), and vice versa in bear markets ($b^{bear}>0$). Table 4 reports the estimation results of Model (3).

- Please insert TABLE 4 approximately here -

As expected, the coefficient b^{bull} is significantly negative, while the coefficient b^{bear} is significantly positive. Significance levels and estimated coefficients are very similar to those of the subsample approach. This lends further support to our hypothesis that the relative strength of employment and compensation incentives is determined by the market phase.

Using this approach, we can re-assess the temporal stability of our results by looking at subsamples including bull as well as bear markets instead of just looking at subsamples consisting of bull or bear markets exclusively. We separate the sample into the two subperiods 1980 to 1996 and 1997 to 2003. This results in subsamples of approximately equal size with respect to the number of observations. Estimation results for these subsamples are reported in the last two Columns of Table 4. Results indicate that the diametrical risk taking behaviour is stable over the time: independent of the underlying subperiod, losers increase risk more than winners in bull markets, while the opposite is true in bear markets.[13]

4.5 Alternative Explanations

Earlier studies that do not differentiate between bull and bear markets find contradictory results. Only few studies address the temporal instability with respect to the influence of the segment rank on risk taking behaviour. Kempf/Ruenzi (2002) and Jans/Otten (2005) find that losers increase risk more than winners before 1996, and vice versa from 1997 onwards for the U.S. and the U.K. mutual fund market, respectively. They speculate that the publication of the findings on tournament behaviour by Brown/Harlow/Starks (1996) in 1996 might have triggered this change in behaviour. This line of reasoning suggests that the behaviour in all years after 1996 should be uniform and in the opposite direction than in the pre 1996 period. However, our results from the pre- and post 1996 subsamples indicate that there is no uniform behaviour in either period. In both cases the direction of risk adjustment is driven by the market phase. This indicates that the contradictory findings of earlier studies are not due to the publication of Brown/Harlow/Starks (1996), but can be explained by differences in the frequency of bull and bear markets in the respective samples.

As mentioned above, Brown/Harlow/Starks (1996) themselves document some temporal instability in risk taking behavior. They assign the lack of influence of performance on risk taking they find for the pre-1985 period and the strong influence afterwards to ‘industry growth and (increased) investor awareness of fund performance’ (p. 85). However, this argument can not explain diametrical behavior in bull and bear markets in later years as documented here. The industry continued to grow rapidly throughout the 1990s and there is no obvious reason to assume that investor awareness of performance has decreased again in recent years. Thus, it is more likely that varying frequency of bull and bear markets in the pre- and after 1985 subsamples they look at explains the change in the influence of midyear performance on risk taking.

[13] This result also holds for alternative subsample specifications, as long as there is a sufficient number of observations from both bull and bear markets contained.

Overall, our results from this section so far demonstrate that the market phase has a decisive impact on the relative strength of the compensation and employment incentives fund managers face. Neglecting the influence of the market phase can result in misleading inference in empirical studies of managerial risk taking.

4.6 Intended Risk Taking and Risk Limits

Almazan/Carlson/Chapman (2004) show that fund managers are regularly subject to a multitude of restrictions. According to Daniel/Wermers (2000), fund managers often have some kind of yearly risk budget or risk limit. If fund managers face such restrictions, they have to counterbalance unexpected risk realizations by adjusting portfolio risk. To examine the influence of unexpected risk realizations on risk adjustments, we extend Model (3) by adding the risk surprise in the first half of the year as additional control variable. We estimate the following pooled cross-sectional regression with time fixed effects:

$$\begin{aligned}\sigma_{it}^{(2),\text{int}} - \sigma_{it}^{(1)} = {} & a + b^{bull} \cdot rank_{it}^{(1)} \cdot D_t^{bull} + b^{bear} \cdot rank_{it}^{(1)} \cdot D_t^{bear} + c \cdot \left(\sigma_{med,t}^{(2),\text{int}} - \sigma_{med,t}^{(1)}\right) \\ & + d \cdot \left(\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}\right) + \varepsilon_{it}\end{aligned} \tag{4}$$

Model (4) contains the same explanatory variables as Model (3) and additionally the risk surprise, $\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}$, for manager *i* in the first half of year *t*. The risk surprise is defined as the difference between the realized risk, $\sigma_{i,t}^{(1)}$, and the intended risk, $\sigma_{i,t}^{(1),\text{int}}$, in the first half of the year. We expect fund managers to correct the unexpected risk realizations in the first half of the year by adjusting their risk accordingly in the second half of the year, i.e. we expect a negative coefficient *d*. Table 5 summarizes the estimation results of Model (4).

- Please insert TABLE 5 approximately here -

The influence of the risk surprise is negative. We can reject the null-hypothesis that unexpected risk has no influence on the intended risk taking behaviour at the one percent level. Fund managers strongly react to risk surprises in the first half of the year by increasing their risk if they are confronted with a lower realized than intended risk, and vice versa. This confirms the idea that fund managers try to reach some kind of risk target by the end of the year.

Even after controlling for risk surprises, our prior findings regarding the influence of bull and bear markets remain unchanged. We still find strong evidence that the direction of risk taking depends on the market phase. As before, the coefficient b^{bear} is significantly positive, while the coefficient b^{bull} is significantly negative, i.e. losers increase their risk more than winners in bull markets, and vice versa in bear markets.

We now turn to an examination of differences in the impact of risk surprises between positive and negative deviations from intended risk in the first half of the year. While both kinds of deviations from intended risk levels are likely to be counterbalanced by subsequent risk adjustments, positive risk surprises should have a stronger effect. If managers are subject to some kind of risk limit, they have to decrease their portfolio risk to still stay within their risk budget by the end of the year. In contrast, if they face a negative risk surprise, there is no immediate need to adjust risk. To capture differences in the impact of positive and negative risk surprises, we split up the influence of surprises into the case where fund managers have a lower realized risk than intended in the first half of the year and the case where realized risk exceeds intended risk in the first half of the year. We do so by interacting the influence of the risk surprise in Model (4) with a dummy:

$$\begin{aligned}\sigma_{it}^{(2),\text{int}} - \sigma_{it}^{(1)} &= a + b^{bull} \cdot rank_{it}^{(1)} \cdot D_t^{bull} + b^{bear} \cdot rank_{it}^{(1)} \cdot D_t^{bear} + c \cdot \left(\sigma_{med,t}^{(2),\text{int}} - \sigma_{med,t}^{(1)}\right) \\ &\quad + d \cdot \left(\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}\right) + d^{pos} \cdot \left(\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}\right) \cdot D_{it}^{pos} + \varepsilon_{it}.\end{aligned} \tag{5}$$

D_{it}^{pos} equals one, if the risk surprise is positive, i.e. if realized risk exceeds intended risk in the first half of the year, and zero otherwise. It captures the additional impact if the risk surprise is positive as compared to the base case of a negative risk surprise. While we expect some counterbalancing of risk surprises in both cases, readjusting risk will often be mandatory for positive risk surprises. Thus, we expect a stronger impact of positive risk surprises. Consequently, we expect a significant negative coefficient for d as well as for d^{pos}. Estimation results are presented in the last Column of Table 5.

We find a statistically significant negative influence of positive as well as negative risk surprises. Furthermore, the negative estimate for d^{pos} indicates that the response to positive risk surprises is significantly stronger. The estimate is nearly six times as large as the estimate for the base case of a negative risk surprise. This confirms the idea that a positive risk surprise is more severe for fund managers and triggers a more pronounced risk adjustment than a negative risk surprise.

Again, our earlier findings of employment incentives dominating in bear markets and compensation incentives dominating in bull markets remain unaffected by the introduction of the interaction term.

5. Influence of Fund Characteristics on Risk taking

In this section, we analyze whether our findings are robust with regard to the influence of individual fund characteristics. Specifically, we examine whether the fund manager's risk taking behaviour depends on the fund's size, age, turnover, expenses, load-status, number of share classes and investment objective. We question whether winners always increase their risk more than losers in bear markets and whether the opposite is true in bull markets or whether there are some exceptions for special subgroups.

These analyses are added since influences of fund characteristics are possible. For example, fund managers' investment decisions might differ between funds of different size. Fund managers in smaller funds might have more flexibility to gamble. Moreover, they might have a higher incentive to gamble because they want their funds to grow into a reasonable size. Risk taking behaviour might also differ between funds with different load-status. Load fund managers might choose more risk then no-load fund managers, since investors are less likely to take out their money after a bad performance if they have to pay loads (see Daniel/Wermers (2000)). Although it is not clear how these characteristics might interact with the impact of market phases on managerial risk taking, we nevertheless examine their influence to explore the robustness of our previous results.

Therefore, we first estimate Model (5) separately for subsamples of funds with specific characteristics. The estimation results are presented in Table 6. Subsamples are formed based on whether the size (Panel A), age (Panel B), turnover (Panel C) or expenses (Panel F) are above or below the median values of the whole sample.

Funds are also classified according to their load-status (Panel E) and the numbers of share classes they offer (Panel G). If a fund imposes loads, it belongs to the subgroup "Load Funds". Otherwise it belongs to the subgroup "No-Load Funds". Funds with one share class are defined as "Single Class Funds", while funds with more than one share class are defined as "Multiple Class Funds". Additionally, in Panel D funds are grouped by their investment objectives „Aggressive Growth" (AG), „Growth" (G), „Growth and Income" (G+I) or „Income" (I).[14]

- Please insert TABLE 6 approximately here -

Generally, our results show only very minor variations in the level of the rank coefficients. Results are robust independent of the subgroup considered: Neither the size, the age, the turnover, the expenses, the load-status, the number of share classes nor the investment objectives play a decisive role in risk taking behaviour. In bull markets winners increase their risk more than losers, and vice versa in bear markets. This confirms our result from above, that compensation incentives are dominant in bull markets, while employment incentives are dominant in bear markets. All rank coefficients remain significant at the one percent level.

Our results concerning the influence of the risk surprise in the first half of the year are also stable with respect to different fund characteristics: fund managers increase their risk if they are confronted with a lower realized than intended risk. While the sign of the coefficient is usually in the right direction (it is only positive but not significant for the low-turnover subsample of funds), for a few of our subsamples this effect is not statistically significant. However, fund managers always significantly decrease their risk if they are confronted with more realized

[14] For reasons of simplicity, we aggregate the similar investment objectives "Small Company Growth", "Other Aggressive Growth" and "Maximum Capital Gains" into the objective "Aggressive Growth".

than intended risk. This effect is usually significantly stronger in magnitude than the reaction to lower than intended risk realizations. The only exception are low-turnover funds, where we find no significant difference between the impact of positive and negative risk surprises, and “Income Funds”, where we find an unexpected positive impact of negative risk surprises.

Instead of estimating our model for subsamples of funds with specific characteristics, we alternatively include various fund characteristics as control variables in a multivariate model. We estimate the following cross-sectional pooled regression with time fixed effects and segment fixed effects:

$$\begin{aligned}\sigma_{it}^{(2),\text{int}} - \sigma_{it}^{(1)} &= a + b^{bull} \cdot rang(ret)_{it}^{(1)} \cdot D_t^{bull} + b^{bear} \cdot rang(ret)_{it}^{(1)} \cdot D_t^{bear} + c \cdot \left(\sigma_{med,t}^{(2),\text{int}} - \sigma_{med,t}^{(1)}\right) \\ &+ d \cdot \left(\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}\right) + d^{pos} \cdot \left(\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}\right) \cdot D_{it}^{pos} + e \cdot \ln(tna)_{i,t} + f \cdot \ln(age)_{i,t} \\ &+ g \cdot D_{it}^{load} + h \cdot expenses_{i,t} + i \cdot turnover_{i,t} + j \cdot D_{it}^{shareclass} + \varepsilon_{it},\end{aligned} \tag{6}$$

where $\ln(tna)_{i,t}$ and $\ln(age)_{i,t}$ are the natural logarithm of fund size and fund age, respectively, D_{it}^{load} is a dummy indicating whether fund *i* is a load fund or not, $expenses_{i,t}$ and $turnover_{i,t}$ are the expense ratio and the turnover ratio of fund *i*, respectively, and $D_{it}^{shareclass}$ is a dummy that takes on the value one if the fund is a multiple-share class fund, and zero otherwise. Finally, we also include the realized standard deviation in the first half of the year, $\sigma_{it}^{(1),T(A)}$, to control for potential mean reversion in fund risk (Koski/Pontiff (1999)). Estimation results are summarized in Table 7.

- Please insert TABLE 7 approximately here -

Our main results remain unaffected. We still find compensation incentives to dominate in bull markets and bear incentives to dominate in bear markets. The influence of risk surprises is also unchanged. It is generally negative and significantly more pronounced for positive risk surprises. Most of the control variables are insignificant. Only size and turnover have a statistically significant but economically small influence on risk taking. The influence of risk in the first half of the year is significantly negative. This indicates mean reversion in fund risk and confirms the findings of Koski/Pontiff (1999). Adding the control variables has only little impact on the R^2 of the model.

Overall, our findings in this section suggest that our results on the influence of market phases on risk taking and re-adjustment of portfolio risk in response to risk surprises are not driven by individual fund characteristics.

6. Conclusion

Mutual fund managers face various incentives that have an impact on their risk taking. While incentives arising from the behaviour of mutual fund investors have been studied in great detail (see, e.g., Brown/Harlow/Starks (1996), Elton/Gruber/Blake (2003), Koski/Pontiff (1999)), there is only little evidence on the impact of employment risk on risk taking. In this paper, we examine both, compensation and employment incentives. Our analysis shows that these two kinds of incentives lead to diametrical predictions regarding managerial risk taking. Compensation incentives should lead midyear losers to increase their risk more than midyear winners in order to catch up with them and profit from large inflows (see Brown/Harlow/Starks (1996)). Employment incentives keep midyear losers from increasing risk in order to prevent a further deterioration of their performance which might entail job loss, while they only have very little or no influence on the behavior of midyear winners.

We show that the relative strength of employment and compensation incentives depends on the market phase. In bull markets aggregate inflows into mutual funds are higher and job opportunities for fund managers are abundant because a lot of new funds are started, while only a few funds exit. Thus, flow-induced compensation incentives are strong and employment risk is negligible. The opposite is true in bear markets, where the thread of dismissal becomes relevant for fund managers and flow-induced compensation incentives are weak because flows into mutual funds are generally low. Therefore, we hypothesize that losers increase risk more than winners in bull market and vice versa in bear markets.

Using data on portfolio holdings of US equity mutual funds and stock returns over the period from 1980 to 2003, this paper is the first to examine the influence of market phases on managerial risk taking. We find that the market phase has a crucial impact on the way managers alter their risk dependent on their midyear performance. In bull markets, midyear losers tend to increase their risk more than midyear winners and vice versa in bear markets. These results also help to reconcile contradicting results presented in earlier studies. Furthermore, we can show that not only the sign, but also the extent of the midyear market return is relevant for the strength of compensation incentives and employment incentives. Accordingly, risk adjustment is more pronounced if the market return is more extreme.

We also find that managers strongly react to unexpected risk realizations in the first half of the year. They counterbalance such risk surprises by adjusting their risk in the second half of the year. The adjustment is stronger, if realized risk is higher than initially planed than if it is lower than intended. This is consistent with the idea that many fund managers face some kind of risk limit they must not or do not want to exceed by the end of the year.

Gaining a better understanding of the incentives driving fund managers' behaviour is important, as these incentives can lead to adverse managerial behavior. As Brown/Harlow/Starks (1996) point out, risk-adjustment of fund managers as a response to compensation incentives is not optimal for fund investors. The same is true for risk adjustments due to employment incentives. They are not aimed at building a portfolio with optimal risk-return characteristics from the fund investor's point of view and create additional trading costs, which eventually hurts performance (Bagnoli/Watts (2000), Li/Tiwari (2001)). James/Isaac (2001) show that risk changes due to such incentives can even lead to inefficient price formation in asset markets.

The most important implication of our study for future research on managerial risk taking is that temporal variations of compensation and employment incentives should not be neglected. Our results show that this can lead to misleading results and eventually erroneous conclusions in studies analyzing the behavior of fund managers. However, we think that these finding also have broader implications for studies on the behavior of managers of corporations in general. In the corporate world the business cycle might play a role similar to the role played by bull and bear markets in this paper. For example, it is likely that employment risk is only a minor concern for managers in a boom period, while it might seriously impact their decisions in a recession. We think that analyzing the impact of business cycles on the incentives corporate managers face might offer an interesting avenue for future research.

Appendix: Matching Process

We start our merging procedure by matching the stocks from the CRSP U.S. Stock database with the holdings data from the Thomson Financial database based on the stocks' CUSIP identifier. Matching the holdings data from Thomson Financial and the mutual fund data from CRSP is not as straightforward. We start by aggregating multiple share classes of the same fund in the CRSP data.[15] Next, the holdings data from Thomson Financial are adjusted for obvious data errors. Especially, we separate identifier numbers which are allocated twice to different funds and combine different identifier numbers allocated to the same fund. As a result, every fund gets assigned a new fund identifier number, which is unique over the whole history of the fund. Then, the aggregated CRSP fund data are matched with the adjusted Thomson Financial fund data. Unfortunately, there is no unique common identifier used in both databases for the whole time period. Since 1999, both CRSP and Thomson Financial provide ticker data. Therefore, we initially match the databases using ticker data for the years 1999 to 2003 and extrapolate the match for the prior years.[16] Beginning in 1975, we then consider the funds' names for our matching process. An algorithm which identifies identical strings and abbreviations is applied. This is necessary, because the CRSP database comprises a 50-character text field for the funds' names, while Thomson Financial provides a 25-character text field. Finally, we check the validity of this matching procedure by comparing total net assets and investment objective information from both data sources for the matched funds.

[15] Most data items are aggregated by weighting the respective number for each share class with the total net assets of this share class. For some variables, other aggregation methods are used. For example, the age of each fund is computed as the age of the oldest share class. The aggregation procedure is similar to the one used by Wermers (2000).

[16] The procedure is similar to the one used by Gaspar/Massa/Matos (2006).

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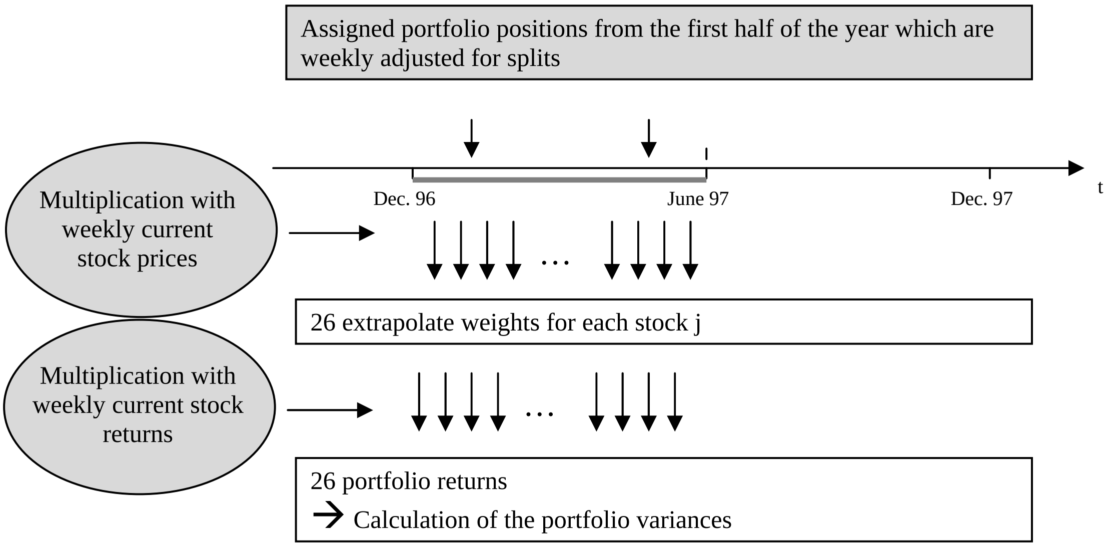
Figure 1

Panel A: Calculation of Realized Standard Deviation in the first half of the year

This figure illustrates the calculation of the realized standard deviation in the first half of the year, $\sigma_{it}^{(1)}$, using the year 1997 as an example.



Panel B: Calculation of Intended Standard Deviation in the second half of the year

This figure illustrates the calculation of the intended standard deviation in the second half of the year, $\sigma_{it}^{(2),\text{int}}$, using the year 1997 as an example.

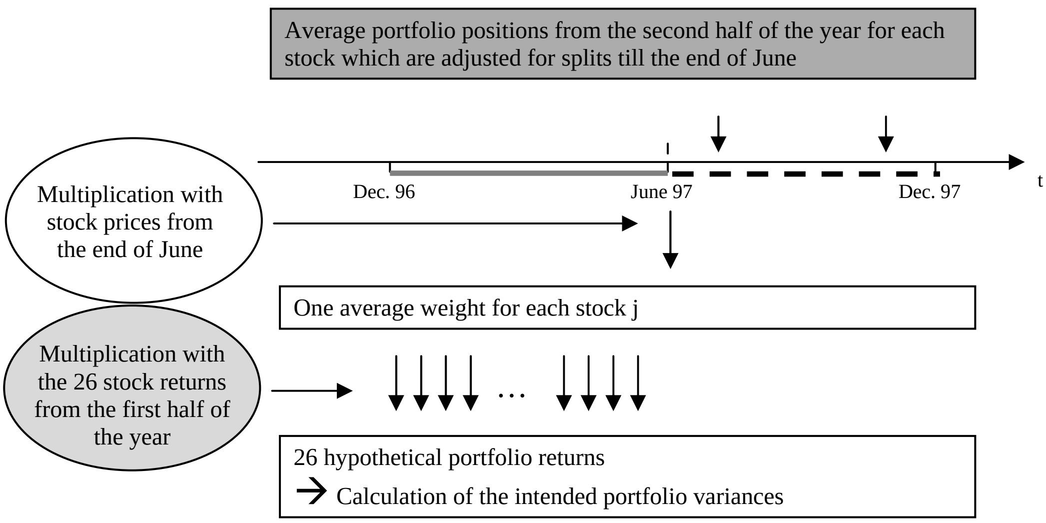


Figure 2

Relationship between the Rank Coefficient and the Midyear Return of the CRSP-Index

The following graphs plot the midyear returns of the CRSP-Index as well as the rank coefficients b of the different years from Model (1) which reads:

$$\sigma_{it}^{(2),\text{int}} - \sigma_{it}^{(1)} = a + b \cdot rank_{it}^{(1)} + c \cdot \left(\sigma_{med,t}^{(2),\text{int}} - \sigma_{med,t}^{(1)}\right) + \varepsilon_{it}\,. \tag{1}$$

Observations are sorted in ascending order based on the midyear return of the CRSP-Index. Panel A plots the relationship for all yearly coefficients, while Panel B plots the same relationship for the significant coefficients only.

Panel A: Rank Coefficient and Midyear Return of the CRSP-Index – All Coefficients

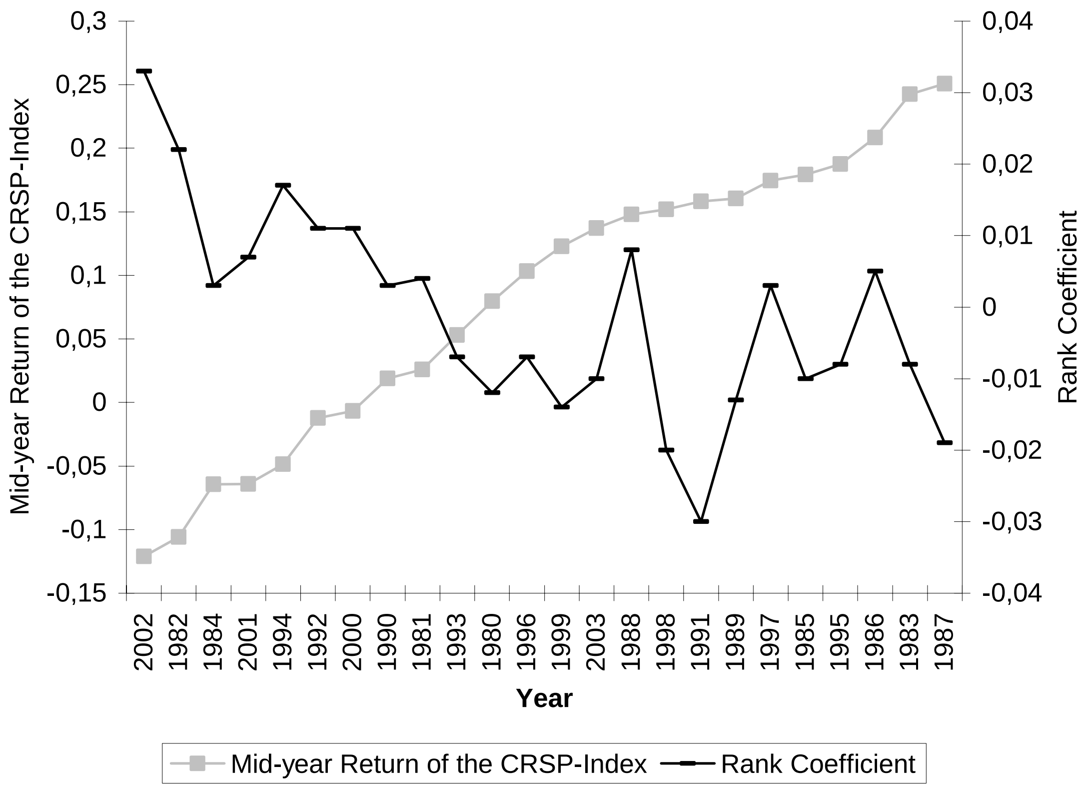


Figure 2
(continued)

Panel B: **Rank Coefficient and Midyear Return of the CRSP-Index – Significant Coefficients only.**

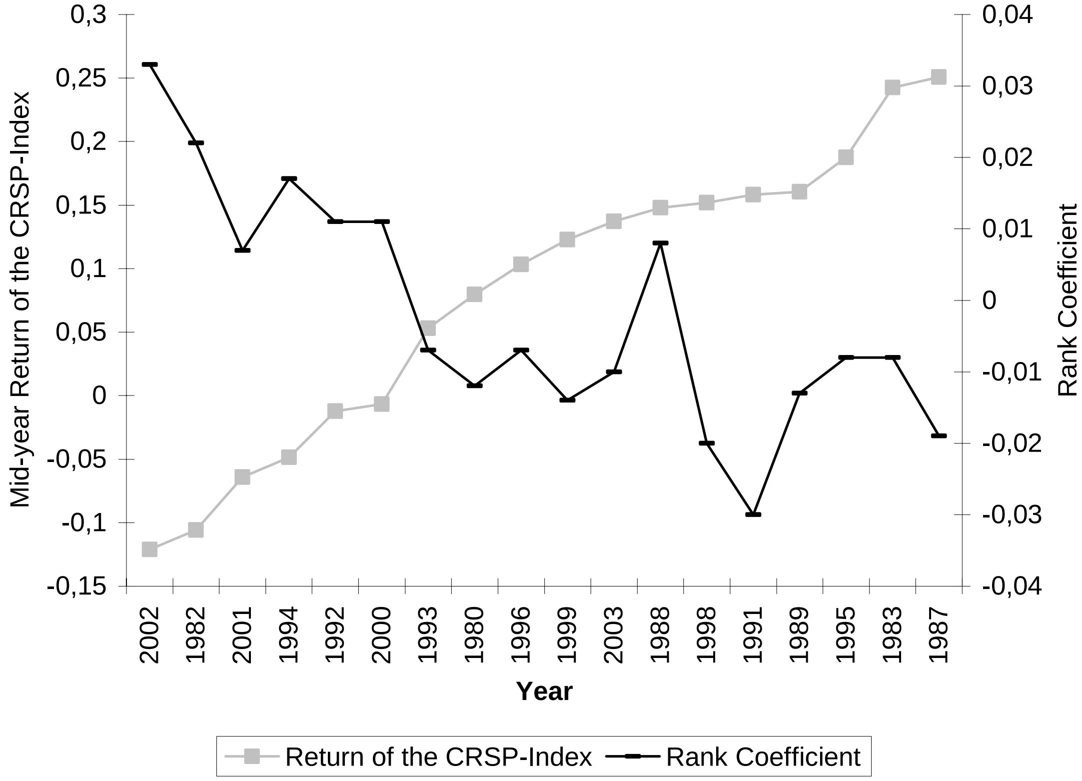


Table 1

Summary Statistics

This table reports the summary statistics of the sample funds for the period from 1980 to 2003. The sample consists of actively managed equity funds. It contains observations from our merge of the U.S. Stock database with the Thomson Financial Mutual Fund Holdings database and the CRSP Survivor-Bias Free U.S. Mutual Fund database. For each sample year, it provides fund counts, average age, the mean total net assets (TNA) and the mean turnover ratio of the funds. Separated share classes of a single fund listed in CRSP mutual funds database are combined based on the last year's total net assets. Individual Share classes are not counted separately. In the last two columns, the table reports the midyear return and the return p.a. of the value-weighted index for all securities traded at the NYSE, AMEX and NASDAQ (CRSP-Index).

Year	Number of Funds	Average Age (in Years)	Mean TNA (in Mio. USD)	Mean Turnover (in %)	Midyear Return of the CRSP-Index (in %)	Return p.a. of the CRSP-Index (in %)
1980	254	24	181	71,45	7,96	32,01
1981	241	25	163	66,21	2,60	-3,04
1982	260	26	186	76,29	-10,57	19,89
1983	272	26	249	78,22	24,24	21,68
1984	297	24	234	73,55	-6,44	2,98
1985	322	24	297	82,86	17,92	31,11
1986	354	23	341	83,58	20,84	15,92
1987	408	21	357	93,95	25,08	1,99
1988	471	19	326	78,09	14,80	17,47
1989	520	19	392	73,32	16,05	28,53
1990	462	20	387	83,06	1,90	-6,07
1991	558	19	482	n.a.	15,82	33,79
1992	614	18	540	74,62	-1,21	8,79
1993	671	17	650	76,75	5,30	11,92
1994	909	13	538	76,82	-4,85	-0,83
1995	1.081	13	713	87,68	18,77	35,03
1996	1.126	13	904	91,57	10,32	21,21
1997	1.295	13	1.129	87,29	17,45	30,30
1998	1.461	12	1.184	89,26	15,20	22,01
1999	1.552	12	1.399	92,98	12,29	26,55
2000	1.367	12	1.464	88,28	-0,68	-11,18
2001	1.710	12	1.146	106,16	-6,41	-11,33
2002	1.493	12	841	103,46	-12,10	-20,93
2003	1.226	13	1.164	94,58	13,70	33,35
Total	18.924	15	871	88,25	8,25	14,21

Table 2

Intended Risk Taking in Bull and Bear Markets: Subsample Approach

Panel A presents the coefficients of the following regression estimated with time fixed effects for subsamples of bull markets and bear markets as well as for the whole sample:

$$\sigma_{it}^{(2),\text{int}} - \sigma_{it}^{(1)} = a + b \cdot rank_{it}^{(1)} + c \cdot \left(\sigma_{med,t}^{(2),\text{int}} - \sigma_{med,t}^{(1)} \right) + \varepsilon_{it} \qquad (1)$$

In this model, $rank_{it}^{(1)}$ is the relative rank of fund *i* in its segment based on raw returns in the first half of the year *t*. $\sigma_{it}^{(1)}$ is the realized standard deviation of the funds' portfolio in the first half of year *t*. $\sigma_{it}^{(2),\text{int}}$ is the intended standard deviation of the funds' portfolio in the second half of year *t*. Therefore, $\sigma_{it}^{(2),\text{int}} - \sigma_{it}^{(1)}$ is the intended funds' change in standard deviations from the first to the second half of year *t*. Similarly, $\sigma_{med,t}^{(2),\text{int}} - \sigma_{med,t}^{(1)}$ is the change in segment standard deviations which is calculated as the difference between the median standard deviations in the first and the second half of year *t*. The subsamples of bull and bear markets are formed based on whether the midyear return of the value-weighted index consisting of all securities traded at the NYSE, AMEX and NASDAQ (CRSP-Index) is positive (bull market) or negative (bear market). The last two rows contain the adjusted R^2 and the number of observation for each regression. Panel B reports the coefficients of the same regression estimated separately for each year from 1980 to 2003. The last three columns present the adjusted R^2, the number of observations and whether the respective year is classified as a bull or bear market. In both Panels, ***, **, and * indicate significance at the one, five, and ten percent level, respectively. t-values are reported in parentheses.

Panel A: Bull Markets vs. Bear Markets

Independent Variable	Dependent Variable $\sigma_{it}^{(2),\text{int}} - \sigma_{it}^{(1)}$		
	Bull Markets	Bear Markets	Whole Sample
$rank_{it}$	-,009 ***	0,016 ***	-,000
	(-12,891)	(10,497)	(-,517)
$\sigma_{med,t}^{(2),\text{int}} - \sigma_{med,t}^{(1)}$	0,901 ***	0,988 ***	0,947 ***
	(17,400)	(13,489)	(22,025)
Adj. R^2	0,168	0,132	0,149
Observations	12.274	6.650	18.924

Table 2
(continued)

Panel B: Yearly Regressions, Dependent Variable $\sigma_{it}^{(2),\text{int}} - \sigma_{it}^{(1)}$

Year	$rank_{it}$	Adj. R^2	Observations	Market Phase
1980	-,012 **	0,035	254	Bull
1981	0,004	0,001	241	Bull
1982	0,022 ***	0,142	260	Bear
1983	-,008 **	0,010	272	Bull
1984	0,003	-,005	297	Bear
1985	-,010	0,049	322	Bull
1986	0,005	0,003	354	Bull
1987	-,019 ***	0,058	408	Bull
1988	0,008 ***	0,016	471	Bull
1989	-,013 ***	0,094	520	Bull
1990	0,003	0,012	462	Bull
1991	-,030 ***	0,223	558	Bull
1992	0,011 ***	0,181	614	Bear
1993	-,007 ***	0,043	671	Bull
1994	0,017 ***	0,122	909	Bear
1995	-,008 ***	0,064	1.081	Bull
1996	-,007 ***	0,024	1.126	Bull
1997	0,003	0,055	1.295	Bull
1998	-,020 ***	0,061	1.461	Bull
1999	-,014 ***	0,033	1.552	Bull
2000	0,011 **	0,009	1.367	Bear
2001	0,007 *	0,038	1.710	Bear
2002	0,033 ***	0,137	1.493	Bear
2003	-,010 ***	0,029	1.226	Bull

Table 3

Relationship between the Rank Coefficient and the Midyear Return of the CRSP-Index

This table contains estimation results from the following regression:

$$b_t = \alpha + \beta \cdot ret_t^{CRSP-Index} + \varepsilon_t. \qquad (2)$$

In this model, b_t is the yearly rank coefficient that is reported in Panel B of Table 2 and $ret_t^{CRSP-Index}$ is the yearly return of the CRSP-Index in the first half of year *t*. The last two columns present the adjusted R^2 and the number of observations. ***, **, and * indicate significance at the one, five, and ten percent level, respectively. t-values are reported in parentheses.

Independent Variable	Dependent Variable b_t	
	All Rank Coefficients	Significant Rank Coefficients
$ret_t^{CRSP-Index}$	-,096 *** (-5,147)	-,119 *** (-5,945)
Adj. R^2	0,526	0,669
Observations	24	18

Table 4

Intended Risk Taking in Bull and Bear Markets: Dummy Approach

This table presents the coefficients of the following regression estimated with time fixed effects for the full sample and for the subperiods 1980 to 1996 and 1997 to 2003:

$$\sigma_{it}^{(2),\text{int}} - \sigma_{it}^{(1)} = a + b^{bull} \cdot rank_{it}^{(1)} \cdot D_t^{bull} + b^{bear} \cdot rank_{it}^{(1)} \cdot D_t^{bear} + c \cdot \left(\sigma_{med,t}^{(2),\text{int}} - \sigma_{med,t}^{(1)} \right) + \varepsilon_{it} \quad (3)$$

In this model, $rank_{it}^{(1)}$ is the relative rank of fund *i* in its segment based on raw returns in the first half of year *t*. $rank_{it}^{(1)}$ is interacted with D_t^{bull} or D_t^{bear}, respectively. D_t^{bull} (D_t^{bear}) is a dummy variable which is equal to one, if the midyear return of the value-weighted index for all securities that are traded at the NYSE, AMEX and NASDAQ (CRSP-Index) is positive (non-positive), and zero otherwise. $\sigma_{it}^{(1)}$ is the actual standard deviation of the funds' portfolio in the first half of year *t*. $\sigma_{it}^{(2),\text{int}}$ is the intended standard deviation of the funds' portfolio in the second half of year *t*. Therefore, $\sigma_{it}^{(2),\text{int}} - \sigma_{it}^{(1)}$ is the intended funds' change in standard deviations from the first to the second half of year *t*. Similarly, $\sigma_{med,t}^{(2),\text{int}} - \sigma_{med,t}^{(1)}$ is the change in segment standard deviations which is calculated from the median standard deviations in the first and the second half of year *t*. The last two columns present the adjusted R^2 and the number of observations. ***, **, and * indicate significance at the one, five, and ten percent level, respectively. t-values are reported in parentheses.

	Dependent Variable $\sigma_{it}^{(2),\text{int}} - \sigma_{it}^{(1)}$		
Independent Variable	Full Sample	1980-1996	1997-2003
$rank_{it} \cdot D_t^{bull}$	-,009 ***	-,008 ***	-,011 ***
	(-10,432)	(-10,072)	(-6,728)
$rank_{it} \cdot D_t^{bear}$	0,016 ***	0,014 ***	0,017 ***
	(13,426)	(10,055)	(9,611)
$\sigma_{med,t}^{(2),\text{int}} - \sigma_{med,t}^{(1)}$	0,949 ***	0,831 ***	1,007 ***
	(22,251)	(16,933)	(15,841)
Adj. R^2	0,162	0,202	0,114
Observations	18.924	8.820	10.104

Table 5

Intended Risk Taking and Risk-Limits

This table presents the coefficients of the following regressions estimated with time fixed effects:

$$\begin{aligned}\sigma_{it}^{(2),\text{int}} - \sigma_{it}^{(1)} &= a + b^{bull} \cdot rank_{it}^{(1)} \cdot D_t^{bull} + b^{bear} \cdot rank_{it}^{(1)} \cdot D_t^{bear} + c \cdot \left(\sigma_{med,t}^{(2),\text{int}} - \sigma_{med,t}^{(1)}\right) \\ &\quad + d \cdot \left(\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}\right) + \varepsilon_{it}\end{aligned} \tag{4}$$

$$\begin{aligned}\sigma_{it}^{(2),\text{int}} - \sigma_{it}^{(1)} &= a + b^{bull} \cdot rank_{it}^{(1)} \cdot D_t^{bull} + b^{bear} \cdot rank_{it}^{(1)} \cdot D_t^{bear} + c \cdot \left(\sigma_{med,t}^{(2),\text{int}} - \sigma_{med,t}^{(1)}\right) \\ &\quad + d \cdot \left(\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}\right) + d^{pos} \cdot \left(\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}\right) \cdot D_{it}^{pos} + \varepsilon_{it}.\end{aligned} \tag{5}$$

In these models, $rank_{it}^{(1)}$ is the relative rank of fund *i* in its segment in the first half of the year *t*. $rank_{it}^{(1)}$ is interacted with D_t^{bull} or D_t^{bear}, respectively. D_t^{bull} (D_t^{bear}) is a dummy variable which is equal to one, if the midyear return of the value-weighted index for all securities that are traded at the NYSE, AMEX and NASDAQ (CRSP-Index) is positive (non-positive), and zero otherwise. $\sigma_{it}^{(1)}$ is the actual standard deviation of the funds' portfolio in the first half of year *t*. $\sigma_{it}^{(k),\text{int}}$ is the intended standard deviation of the funds' portfolio in the *k* half of year *t*. Therefore, $\sigma_{it}^{(2),\text{int}} - \sigma_{it}^{(1)}$ is the intended funds' change in standard deviations from the first to the second half of year *t*. Similarly, $\sigma_{med,t}^{(2),\text{int}} - \sigma_{med,t}^{(1)}$ is the change in segment standard deviations which is calculated from the median standard deviations in the first and the second half of year *t*. $\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}$ is the unexpected realized risk in the first half of the year. D_{it}^{pos} is a dummy variable which is equal to one, if $\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}$ is positive, and zero otherwise. The last two columns present the adjusted R^2 and the number of observations. ***, **, and * indicate significance at the one, five, and ten percent level, respectively. t-values are reported in parentheses.

Independent Variable	Dependent Variable $\sigma_{it}^{(2),\text{int}} - \sigma_{it}^{(1)}$	
	Model (4)	Model (5)
$rank_{it} \cdot D_t^{bull}$	-,008 *** (-9,253)	-,008 *** (-9,222)
$rank_{it} \cdot D_t^{bear}$	0,018 *** (15,076)	0,018 *** (15,212)
$\sigma_{med,t}^{(2),\text{int}} - \sigma_{med,t}^{(1)}$	1,021 *** (23,834)	1,005 *** (23,517)
$\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}$	-,071 *** (12,796)	-,021 *** (2,957)
$\left(\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}\right) \cdot D_{it}^{pos}$		-,125 *** (10,534)
Adj. R^2	0,169	0,174
Observations	18.924	18.924

Table 6

Influence of Fund Characteristics on Risk Taking: Subsample Approach

This table reports the coefficients of the following regression estimated with time fixed effects:

$$\sigma_{it}^{(2),\text{int}} - \sigma_{it}^{(1)} = a + b^{bull} \cdot rank_{it}^{(1)} \cdot D_t^{bull} + b^{bear} \cdot rank_{it}^{(1)} \cdot D_t^{bear} + c \cdot \left(\sigma_{med,t}^{(2),\text{int}} - \sigma_{med,t}^{(1)}\right) + d \cdot \left(\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}\right) + d^{pos} \cdot \left(\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}\right) \cdot D_{it}^{pos} + \varepsilon_{it}. \quad (5)$$

for subsamples consisting of funds with specific characteristics. In the above model, $rank_{it}^{(1)}$ is the relative rank of fund *i* in its segment in the first half of the year *t*. $rank_{it}^{(1)}$ is interacted with D_t^{bull} or D_t^{bear}, respectively. D_t^{bull} (D_t^{bear}) is a dummy variable which is equal to one, if the midyear return of the value-weighted index for all securities that are traded at the NYSE, AMEX and NASDAQ (CRSP-Index) is positive (non-positive), and zero otherwise. $\sigma_{it}^{(1)}$ is the actual standard deviation of the funds' portfolio in the first half of year *t*. $\sigma_{it}^{(k),\text{int}}$ is the intended standard deviation of the funds' portfolio in the *k* half of year *t*. Therefore, $\sigma_{it}^{(2),\text{int}} - \sigma_{it}^{(1)}$ is the intended funds' change in standard deviations from the first to the second half of year *t*. Similarly, $\sigma_{med,t}^{(2),\text{int}} - \sigma_{med,t}^{(1)}$ is the change in segment standard deviations which is calculated from the median standard deviations in the first and the second half of year *t*. $\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}$ is the unexpected realized risk in the first half of the year. D_{it}^{pos} is a dummy variable which is equal to one, if $\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}$ is positive, and zero otherwise. We examine subsamples which are formed based on whether the size (Panel A), age (Panel B), turnover (Panel C) or the expense ratio (Panel F) is above or below the respective median values. Funds are also separated based on their load-status (Panel E) and on the numbers of share classes they offer (Panel G). Additionally, funds are grouped by their investment objectives „Aggressive Growth" (AG), „Growth" (G), „Growth and Income" (G+I) and „Income" (I) in Panel D. The last two columns in all Panels present the adjusted R^2 and the number of observations. ***, **, and * indicate significance at the one, five, and ten percent level, respectively. t-values are reported in parentheses.

Panel A: Small Funds vs. Large Funds

	Dependent Variable $\sigma_{it}^{(2),\text{int}} - \sigma_{it}^{(1)}$	
Independent Variable	Small Funds	Large Funds
$rank_{it} \cdot D_t^{bull}$	-,006 ***	-,010 ***
	(-5,101)	(-8,122)
$rank_{it} \cdot D_t^{bear}$	0,016 ***	0,021 ***
	(9,198)	(12,491)
$\sigma_{med,t}^{(2),\text{int}} - \sigma_{med,t}^{(1)}$	0,925 ***	1,084 ***
	(14,618)	(18,761)
$\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}$	-,017	-,025 **
	(-1,571)	(-2,572)
$\left(\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}\right) \cdot D_{it}^{pos}$	-,110 ***	-,141 ***
	(-6,080)	(-8,999)
Adj. R^2	0,164	0,185
Observations	9.462	9.462

Table 6
(continued)

Panel B: Young Funds vs. Old Funds

	Dependent Variable $\sigma_{it}^{(2),\text{int}} - \sigma_{it}^{(1)}$	
Independent Variable	Young Funds	Old Funds
$rank_{it} \cdot D_t^{bull}$	-,007 ***	-,009 ***
	(--5,203)	(-8,096)
$rank_{it} \cdot D_t^{bear}$	0,016 ***	0,020 ***
	(8,090)	(13,897)
$\sigma_{med,t}^{(2),\text{int}} - \sigma_{med,t}^{(1)}$	1,081***	0,900 ***
	(16,193)	(16,380)
$\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}$	-,030 ***	-,014
	(-2,597)	(-1,486)
$\left(\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}\right) \cdot D_{it}^{pos}$	-,119***	-,129 ***
	(-6,483)	(-8,326)
Adj. R^2	0,162	0,189
Observations	8.611	10.305

Panel C: Low Turnover Funds vs. High Turnover Funds

	Dependent Variable $\sigma_{it}^{(2),\text{int}} - \sigma_{it}^{(1)}$	
Independent Variable	Low Turnover Funds	High Turnover Funds
$rank_{it} \cdot D_t^{bull}$	-,005 ***	-,009 ***
	(-5,074)	(-5,825)
$rank_{it} \cdot D_t^{bear}$	0,014 ***	0,021 ***
	(9,620)	(10,687)
$\sigma_{med,t}^{(2),\text{int}} - \sigma_{med,t}^{(1)}$	0,764 ***	1,182 ***
	(13,588)	(16,387)
$\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}$	-,021 **	-,034 ***
	(-2,047)	(-3,050)
$\left(\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}\right) \cdot D_{it}^{pos}$	-,015	-,163 ***
	(-,888)	(-8,896)
Adj. R^2	0,192	0,164
Observations	8.804	8.767

Panel D: Investment Objectives

	Dependent Variable $\sigma_{it}^{(2),\text{int}} - \sigma_{it}^{(1)}$			
Independent Variable	AG	G	G+I	I
$rank_{it} \cdot D_t^{bull}$	-,012 ***	-,007 ***	-,005 ***	-,009 ***
	(-5,158)	(-5,905)	(-3,143)	(-4,962)
$rank_{it} \cdot D_t^{bear}$	0,011 ***	0,024 ***	0,008 ***	0,019 ***
	(3,729)	(13,889)	(3,357)	(8,514)
$\sigma_{med,t}^{(2),\text{int}} - \sigma_{med,t}^{(1)}$	0,775 ***	0,793 ***	0,699 ***	0,181
	(6,753)	(10,158)	(5,467)	(,303)
$\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}$	-,036 **	-,010	0,036	0,060 **
	(-2,359)	(-,765)	(1,437)	(2,176)
$\left(\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}\right) \cdot D_{it}^{pos}$	-,172 ***	-,126 ***	-,188 ***	-,118 ***
	(-6,792)	(-6,434)	(-4,409)	(-3,152)
Adj. R^2	0,218	0,156	0,220	0,125
Observations	4.858	8.783	1.267	2.852

Table 6
(continued)

Panel E: Load Funds vs. No-Load Funds

	Dependent Variable $\sigma_{it}^{(2),\text{int}} - \sigma_{it}^{(1)}$	
Independent Variable	Load Funds	No-Load Funds
$rank_{it} \cdot D_t^{bull}$	-,007 ***	-,010 ***
	(-5,720)	(-7,424)
$rank_{it} \cdot D_t^{bear}$	0,021 ***	0,015 ***
	(13,236)	(8,125)
$\sigma_{med,t}^{(2),\text{int}} - \sigma_{med,t}^{(1)}$	1,066 ***	0,934 ***
	(18,921)	(14,221)
$\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}$	-,026 ***	-,014
	(-2,892)	(-1,207)
$\left(\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}\right) \cdot D_{it}^{pos}$	-,153 ***	-,095 ***
	(-9,925)	(-5,074)
Adj. R^2	0,194	0,152
Observations	10.491	8.429

Panel F: Low Expense Funds vs. High Expense Funds

	Dependent Variable $\sigma_{it}^{(2),\text{int}} - \sigma_{it}^{(1)}$	
Independent Variable	Low Expense Funds	High Expense Funds
$rank_{it} \cdot D_t^{bull}$	-,010 ***	-,007 ***
	(-8,836)	(-5,031)
$rank_{it} \cdot D_t^{bear}$	0,017 ***	0,019 ***
	(10,836)	(10,580)
$\sigma_{med,t}^{(2),\text{int}} - \sigma_{med,t}^{(1)}$	0,966 ***	0,996 ***
	(16,652)	(15,810)
$\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}$	-,026 ***	-,019 *
	(-2,411)	(-1,909)
$\left(\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}\right) \cdot D_{it}^{pos}$	-,079 ***	-,151 ***
	(-4,595)	(-8,979)
Adj. R^2	0,182	0,171
Observations	9.466	9.440

Panel G: Single Class Funds vs. Multiple Class Funds

	Dependent Variable $\sigma_{it}^{(2),\text{int}} - \sigma_{it}^{(1)}$	
Independent Variable	Single Class Funds	Multiple Class Funds
$rank_{it} \cdot D_t^{bull}$	-,008 ***	-,009 ***
	(-7,544)	(-5,225)
$rank_{it} \cdot D_t^{bear}$	0,017 ***	0,020 ***
	(11,133)	(10,320)
$\sigma_{med,t}^{(2),\text{int}} - \sigma_{med,t}^{(1)}$	0,903 ***	1,156 ***
	(16,820)	(16,294)
$\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}$	-,036 ***	-,009
	(-3,616)	(-,832)
$\left(\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}\right) \cdot D_{it}^{pos}$	-,110 ***	-,141 ***
	(-7,001)	(-7,674)
Adj. R^2	0,172	0,168
Observations	12.041	6.883

Table 7

Influence of Fund Characteristics on Risk Taking: Multivariate Approach

This table presents the coefficients of the following regression estimated with time and segment fixed effects:

$$\begin{aligned}\sigma_{it}^{(2),\text{int}} - \sigma_{it}^{(1)} &= a + b^{bull} \cdot rang(ret)_{it}^{(1)} \cdot D_t^{bull} + b^{bear} \cdot rang(ret)_{it}^{(1)} \cdot D_t^{bear} + c \cdot \left(\sigma_{med,t}^{(2),\text{int}} - \sigma_{med,t}^{(1)}\right) \\ &+ d \cdot \left(\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}\right) + d^{pos} \cdot \left(\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}\right) \cdot D_{it}^{pos} + e \cdot \ln(tna)_{i,t} + f \cdot \ln(age)_{i,t} \\ &+ g \cdot D_{it}^{load} + h \cdot expenses_{i,t} + i \cdot turnover_{i,t} + j \cdot D_{it}^{shareclass} + k \cdot \sigma_{i,t}^{(1)} + \varepsilon_{it},\end{aligned} \qquad (6)$$

In these models, $rank_{it}^{(1)}$ is the relative rank of fund *i* in its segment in the first half of the year *t*. $rank_{it}^{(1)}$ is interacted with D_t^{bull} or D_t^{bear}, respectively. D_t^{bull} (D_t^{bear}) is a dummy variable which is equal to one, if the midyear return of the value-weighted index for all securities that are traded at the NYSE, AMEX and NASDAQ (CRSP-Index) is positive (non-positive), and zero otherwise. $\sigma_{it}^{(1)}$ is the actual standard deviation of the funds' portfolio in the first half of year *t*. $\sigma_{it}^{(k),\text{int}}$ is the intended standard deviation of the funds' portfolio in the *k* half of year *t*. Therefore, $\sigma_{it}^{(2),\text{int}} - \sigma_{it}^{(1)}$ is the intended funds' change in standard deviations from the first to the second half of year *t*. Similarly, $\sigma_{med,t}^{(2),\text{int}} - \sigma_{med,t}^{(1)}$ is the change in segment standard deviations which is calculated from the median standard deviations in the first and the second half of the year. $\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}$ is the unexpected realized risk in the first half of the year. D_{it}^{pos} is a dummy variable which is equal to one, if $\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}$ is positive, and zero otherwise. $\ln(tna)_{i,t}$ and $\ln(age)_{i,t}$ are the natural logarithm of fund size and fund age, respectively, D_{it}^{load} is a dummy indicating the load status of fund *i* and which takes on the value one, if any of the share classes of the fund charges a load, and zero otherwise, $expenses_{i,t}$ and $turnover_{i,t}$ are the expense ratio and the turnover ratio of fund *i*, respectively, and $D_{it}^{shareclass}$ is a dummy that takes on the value one if the fund is a multiple-share class fund, and zero otherwise. Finally, we also include realized fund standard deviation in the first half of the year, $\sigma_{it}^{(1)}$, to control for potential autocorrelation of fund risk. The last two columns present the adjusted R^2 and the number of observations. ***, **, and * indicate significance at the one, five, and ten percent level, respectively. t-values are reported in parentheses.

Table 7
(continued)

Independent Variable	Dependent Variable $\sigma_{it}^{(2),\text{int}} - \sigma_{it}^{(1)}$
$rank_{it} \cdot D_t^{bull}$	-,006 *** (-6,616)
$rank_{it} \cdot D_t^{bear}$	,014 *** (10,757)
$\sigma_{med,t}^{(2),\text{int}} - \sigma_{med,t}^{(1)}$	1,072 *** (22,466)
$\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}$	-,020 ** (-2,520)
$(\sigma_{i,t}^{(1)} - \sigma_{i,t}^{(1),\text{int}}) \cdot D_{it}^{pos}$	-,067 *** (-4,775)
$\sigma_{it}^{(1),T(A)}$	-,053 *** (-9,598)
Ln_TNA	-,000 ** (-2,319)
Ln_Age	,000 (,678)
Load-Dummy	,000 (,713)
Expense	-,018 (-,462)
Turnover	-,001 *** (-6,060)
Share class-Dummy	,001 (1,233)
Segment Fixed Effects	Yes
Adj. R^2	0,174
Observations	17.570