Bond fund disappearance:
What's Return got to do with it?*

MARTIN ROHLEDER[1], HENDRIK SCHOLZ[2] and MARCO WILKENS[3]
[1, 3]*University of Augsburg*; [2]*University of Erlangen-Nuernberg*;

Working Paper. 01.11.2011 (first version: 17.02.2011)

Abstract. In 1993, Blake, Elton and Gruber state in their seminal paper on bond fund performance that survivorship bias is unimportant for bond funds. Many bond fund studies have since been published without treating survivorship bias or bond fund disappearance despite the fact that the statement is based upon biased data. To fill this gap, we are the first to comprehensively analyze disappearance and survivorship bias of bond funds. As key determinants we identify size, flows and expenses. Returns have very little influence on disappearance. However, we find statistically significant and economically relevant survivorship bias, especially for certain asset classes.

Keywords: fund disappearance, bond mutual fund performance, survivorship bias
JEL Classification: G 11, G 12

* We would like to thank Oliver Entrop and the participants of the HVB doctoral student seminar 2011 in Nuernberg, Germany, the participants of the International doctoral student seminar 2011 in Vaduz, Liechtenstein, and the participants of the 9th ATINER International Conference on Business 2011 in Athens, Greece, for helpful comments and suggestions. Also, we would like to thank Isabel Canette for technical support. We are responsible for any remaining errors.

1. Introduction and literature

In recent years the market for bond funds has experienced dramatic growth both in the number of funds available for investment and in the volume of assets under management (e.g., Ferson et al., 2006; Huij and Derwall, 2008; Chen et al., 2010; Cici and Gibson, 2010). Consequentially, there has also been a growing body of academic research on bond mutual funds. However, in comparison to equity mutual funds where a huge number of studies have been conducted since the 1960s (e.g., Sharpe, 1966; Treynor and Mazuy, 1966; Jensen, 1968), this area of research merely passed its teenager years (e.g., Huij and Derwall, 2008; Chen et al., 2010; Cici and Gibson, 2010). Starting only in the early 1990s, Blake et al. (1993) where the first to thoroughly assess the performance of bond mutual funds finding that actively managed bond funds on average, like equity funds, under-perform passive benchmark portfolios net of fees while performing on par on a gross-of-fees basis. A number of empirical studies were to follow mainly concentrating on the performance of different groups of bond mutual funds, on performance persistence in the bond fund market, and on different methods to assess the performance of bond mutual funds.

Surprisingly, an issue that has not been researched in greater detail is the fund characteristics leading to bond fund disappearance.[1] From the literature on survivorship bias in equity mutual funds it is well known that fund disappearance can cause seriously biased results as non-survivors show systematically inferior performance compared to survivors (e.g., Grinblatt and Titman, 1989; Brown et al., 1992; Malkiel, 1995; ter Horst et al., 2001; Carhart et al., 2002; Deaves, 2004; Rohleder et al., 2010). In their seminal paper on bond fund performance, Blake et al. (1993) state that survivorship bias is less important to bond funds because performance is less variable and because fewer bond funds disappear. Since then, many researchers using potentially survivorship biased data in their bond fund studies

[1] Zhao (2005) studies exit decisions in the mutual fund industry including equity, hybrid, and bond funds based upon quarterly data. However, he concentrates on differences and commonalities of different exit forms (liquidation and merger within and without the fund family) rather than on the distinct features of different asset classes.

refer to this statement without further investigation saying that performance overstatement through survivorship bias does not harm their findings of anyway significantly negative performance (e.g., Elton et al., 1995; Detzler, 1999; Silva et al., 2005; Polwitoon and Tawatnuntachai, 2006).

As it has not been done in a comprehensive way before, we investigate the disappearance of bond funds as well as survivorship bias in the bond fund industry and the economic relations behind it because of several reasons. First, there were very few funds available for investment in the early 1990s while today there are a large number of funds competing for investors.[2] To attract new investors active bond fund managers today can use a variety of tools like interest rate derivatives or exploiting liquidity differences to out-perform their peers, thereby increasing the variability of bond fund returns (e.g., Ferson et al.; 2006). As a consequence, more bond funds disappear, causing survivorship bias to be of potentially growing importance. Second, there are a number of asset classes subsumed under bond funds showing very different characteristics. Mortgage-backed bond funds include option-like features due to uncertain maturities because homeowners have the right to sell or refinance their homes at any time (Huij and Derwall, 2008). Corporate bond funds, especially low-grade or high-yield bond funds, show equity-like characteristics (Cornell and Green, 1991; Philpot et al., 2000; Dietze et al., 2009). A similar argument applies to high-yield municipal bond funds (e.g., Kihn, 1996). In addition, municipal bond funds are majorly tax-exempt giving them a special status within the bond fund industry (e.g., Redman and Gullet, 2007; Boney and Comer, 2010). These distinct features potentially increase the variability of fund returns causing survivorship bias to be more important to certain asset classes. Third, although survivorship bias is not a severe problem for studies treating US based bond funds as the CRSP database covers both survivors and non-survivors, it is important to understand the economic relations causing bond funds to disappear because studies outside the US are predominantly plagued by survivorship bias (e.g., Gallagher and Jarnecic, 2002; Silva et al., 2005; Dietze et al., 2009). In addition, biased results are inevitable in some studies due to a

[2] Blake et al., 1993, investigate the performance of 223 funds in their large sample not accounting for multiple share classes. Our sample includes 3,192 funds already adjusted for multiple share class funds.

certain methodology, e.g. in the performance persistence literature where funds have to survive subsequent periods (e.g., Droms and Walker, 2006; Philpot et al., 1998 and 2000) or when individual funds are considered and the requirement of long return histories systematically excludes more non-survivors than survivors (e.g., Polwitoon and Tawatnuntachai, 2006). Fourth, Zhao (2005) finds that the factors leading to the disappearance of bond funds are not different to the factors leading to the disappearance of equity funds. Among others, Brown and Goetzmann (1995) find that inferior returns play a crucial role in the disappearance of equity funds leading to significant survivorship bias. This is in contrast to the statement of Blake et al. (1993). Last, Blake et al. (1993) estimate survivorship bias based upon already biased data. Their main sample of 41 funds includes all funds existing in 1979 which are followed through end of 1988 including five non-survivors but excluding all new funds. The second sample of 233 funds includes all funds existent in 1991 independent from their fund start ("end-of-sample survivors", e.g., Carhart et al, 2002). Their results might therefore be imprecise.

In order to fill this gap, we thoroughly analyze the disappearance of bond mutual funds in the sample period from 1993-2009 and in different sub-periods. Moreover, we split the sample into different asset classes representing corporate, government, mortgage backed, municipal, money market, and "general" bond funds. For these asset classes we also analyze the performance of different sub-groups representing survivors/non-survivors and initial/new funds, as well as survivorship bias and survivorship bias differences. Moreover, we assess in detail the performance of size-decile portfolios and different groups of non-survivors to uncover the economic relations behind the disappearance of bond funds.

Our empirical results clearly indicate that fund size is the predominant factor influencing fund disappearance such that larger funds survive while smaller funds disappear. Fund flows have substantial impact on fund disappearance such that funds with high outflows are more likely to disappear. Also, the expense ratio is of some importance as funds with higher expenses are more likely to disappear while funds with lower expense ratios survive. Surprisingly, returns have only very little influence on disappearance. We find only small absolute survivorship bias compared to the one documented for equity funds. However, relative to the unbiased performance survivorship bias is still economically highly significant as it overstates average bond fund performance by up to 40 %. For some asset classes the overstatement even amounts to more than 400 %.

The remainder of the paper is organized as follows. Section 2 describes the methods applied to analyze the disappearance of bond funds as well as the models used to assess the performance of different bond fund portfolios. Here, we also describe the construction of the different fund portfolios. Section 3 introduces the database and reports summary statistics from which we derive hypotheses for our empirical study. Section 4 presents empirical results. Section 5 concludes.

2. Methodology

2.1 PROBIT ANALYSIS OF FUND DISAPPEARANCE

The main focus of our empirical study is on the determinants of US bond mutual fund disappearances, which we analyze using differently specified probit models in reference to Brown and Goetzmann (1995) and Rohleder et al. (2010). We apply these models on different sets of pooled yearly non-overlapping observations of 3,037 individual funds, subdivided into different asset classes and different time periods. Our binary dependent variable Dis_{it} equals 1 in the case of fund disappearance and 0 in the case of survival. The probit model is given by:

(1)

As explanatory variables x_{it} we use (lagged) returns, size, age, (lagged) flows, and expense ratios, which we preprocess majorly referring to Brown and Goetzmann (1995). In terms of the expense ratio we use the yearly expense ratio given by CRSP in t-1m (the month prior to the reference date). [3] As variable for fund age we use count of months since inception in t-1m.

[3] For disappeared funds the month of reference for yearly observations is the month of disappearance. E.g., if a fund disappears in July 1999 the reference for this fund is July such that in the years before 1999 this fund counts as survivor with observations in July. For surviving funds the month of reference for yearly observations is December because 12/2009 is our last data point, thereby maximizing the

In terms of the fund returns we use the yearly relative return. It is given by a funds cumulative return over one year minus the cumulative average return of all funds over the same period. We observe this lagged variable in *t*-1*y* (1-year period prior to fund reference), *t*-2*y* (the year prior to *t*-1*y*) and *t*-3*y* (the year prior to *t*-2*y*), respectively. In addition and for robustness, we also use the 5-year cumulative relative return of the fund (*t*1-5*y*) because it could be rational for fund families to base their closing decisions upon return histories longer than 1 year. Analogously constructed are lagged relative fund flows for *t*-1*y*, *t*-2*y*, and *t*-3*y* which are given by the cumulative flow to the fund over one year minus the average cumulative flow to all funds over the same period.

As our first size variable we use the relative size in *t*-1*m* given by the TNA of the fund minus the average TNA of all funds in the same month (e.g. Brown and Goetzmann, 1995). Alternatively, we use as our second size variable the log TNA of the fund in *t*-1*m* in order to eliminate extreme outliers. In addition, we use dummy variables for small funds (lower third in a given month) and large funds (upper third in a given month) to interact with returns and flows in order to account for different relations depending on the size of a fund (e.g., Rohleder et al., 2010). Table I reports correlation coefficients between all explanatory variables suggesting multicollinearity to be of minor importance.

[Insert Table I here.]

2.2 PERFORMANCE ANALYSIS OF BOND FUND PORTFOLIOS

Portfolio Construction

For our empirical analysis on bond fund performance we use equal- and value-weighted monthly return time series of fund portfolios (or "fund of funds", e.g., Cornell and Green, 1991) due to some very important advantages. First, we can use data on all 3,192 funds regardless of the length of the funds return history while individual funds existing for less than 3 years would usually be excluded from the

---

number of observations. As more than half of all funds in our sample disappear, the yearly observations are distributed over all months reducing a potential bias (calendar effects, etc.).

sample (e.g., Philpot et al, 1998; Polwitoon and Tawatnuntachai, 2006). Also, we can use funds with punctually missing return data as long as the aggregate portfolio time series is complete. Second, we can use monthly TNA directly to value-weight fund returns cross-sectionally in the portfolio. This is not possible for individual fund performance measures as the average size of a fund is not stationary, especially not for fast growing new funds and decreasing disappeared funds. Third, the aggregate time series of different fund portfolios cover identical time periods such that a comparison between different portfolios cannot be biased by the funds existing in different time periods or market climates (e.g., Scholz and Schnusenberg, 2009). Fourth, by aggregating monthly returns the “length”-weight of a fund in the portfolio corresponds directly to its time series length. By contrast, when averaging individual performance measures funds with shorter return histories are over-weighted.

For our basic performance and survivorship bias analysis we split our full sample of 3,192 US bond mutual funds into the 8 sub-groups representing different survivor/non-survivor and different initial/new fund, as well as into 6 sub-groups representing different asset classes. In addition, we assess sub-periods cutting the period in more or less equal parts (1993-2001 and 2002-2009) and separating the periods before and during the 2007 financial crisis (1993-2006 and 2007-2009). For all sub-periods we use period specific survivor/non-survivor and initial/new identifications. See Table A.1 in the Appendix for a detailed overview.

For our analysis of the performance of size-deciles we construct decile portfolios by monthly ranking all existing funds by their beginning of month TNA and aggregating the monthly returns of all funds allocated to a respective rank-decile. This method assures that the results do not suffer from forward looking bias. In addition to the performance of the deciles, we report decile-specific disappearance rates. These describe the rate with which a fund belonging to a certain size-decile at any point in time disappears in the next month (t+1m), within the next 1-year period (t+1y), or within the next 2-year period (t+2y), respectively. We calculate these rates by counting for each size-decile the number of months for which non-survivors were allocated to the decile in their last month (t+1m), during their last year (t+1y), or during their last two years (t+2y), respectively. The results are then divided by the total number of months any fund was allocated to the respective size-decile.

For our analysis of the performance of non-survivors we construct portfolios of non-survivors according to the time frame before fund disappearance. Specifically, we split the return time series of individual funds into five sub-segments corresponding to the last year, the second to last year, the third to last year, and the fourth to last year of existence, as well as the rest of the time series. Identical segments of all funds are allocated to the same portfolio. As funds disappear throughout the whole sample period we observe all fund segments during the whole sample period, except for the last 4 years of the dataset as we do not know which funds disappear in the years 2010 through 2013. Therefore, we limit our dataset to the time period from 01/1993 through 12/2005 to compare the segment-specific return time series. Also, instead of using the non-survivor returns directly, we calculate return differences between the non-survivor portfolios and the end-of-sample survivor portfolio in order to have a scale showing directly whether and when non-survivors out- or under-perform survivors.

Performance Measures

We use five commonly used performance measures to assess the performance of our bond mutual fund portfolios. The first is the monthly mean excess return MER_p which is simply the time series average return R_{pt} of a fund portfolio p in excess of the risk free rate of return R_{ft}. It is given by

$$- \qquad (2)$$

For the construction of more complex models to measure the performance of the bond fund portfolios we refer to the seminal paper of Blake et al. (1993). Considering the return of a bond index to proxy for the return of a passive portfolio a linear factor model compares the excess return of a fund portfolio to the excess return of one or more indices while accounting for differences in risk that may exist between a fund and an index (Blake et al., 1993). In the case of a single factor or index as explanatory variable, this type of model is given by

(3)

where α_p is the average risk-adjusted excess return of fund portfolio p, β_p is the sensitivity of the excess return of portfolio p to the excess return of index I, and ε_{pt} is a normally distributed residual term with zero mean (e.g., Jensen, 1968). In the case of multiple factors or indices as explanatory variables this type of model is given by

(4)

where j = 1, …, J denotes the indices used to access the performance of fund portfolio p. We use this approach in three of our models, a single index model (SIM) and two multi index models (MIM-Risk and MIM-Maturity). In SIM we use a broad market index represented by the Barclays Capital US Aggregate Bond Index as the most widely used broad US bond index. In MIM-Risk we use specialized indices representing five different asset classes with government (Barclays Capital US Aggregate Government), corporate (Barclays Capital US Corporate Investment Grade), mortgage backed (Barclays Capital US Mortgage Backed), municipal (Barclays Capital US Municipal), and high yield (Barclays Capital US High Yield Composite) as explanatory variables. In MIM-Maturity we further split the corporate and government indices into maturity components such that we have a seven index model where the Barclays Capital US Corporate Intermediate and Barclays Capital US Corporate Long indices account for corporate bonds (e.g., Blake et al., 1993). For the government component we construct an intermediate term by equal-weighting the Merrill Lynch US Agencies 3-5Y and the Merrill Lynch US Agencies 5-7Y Index. For the government long-term component we equal-weight the Merrill Lynch US Agencies 7-10Y, the Merrill Lynch US Agencies 10-15Y, and the Merrill Lynch US Agencies 15Y+ Index. For a detailed overview of the models see Table A.2 in the Appendix. Table II shows correlation coefficients between all explanatory variables suggesting that multicollinearity is of minor importance.

[Insert Table II here.]

SIM and MIM models, however, have a shortcoming in that they are not able to account for institutional and legal restrictions to the investment style of a mutual fund.

Unlike hedge funds, mutual funds are not allowed to sell short and mutual fund are not allowed to leverage their investments. In practice this means that the sensitivities β_{pj} cannot become negative and the sum of sensitivities must add to unity. To overcome this shortcoming, Sharpe (1988, 1992) introduces a constrained asset class factor model (ACF), which is given by

(5)

With

where I_{J+1} is the risk free rate of return R_f which is incorporated as an additional independent variable in order to keep the constraints simple (Dietze et al., 2009). We use this approach in our ACF-Risk model which is based directly upon the unrestricted MIM-Risk model. Both models therefore show exactly the same results for α_p and β_{jp} if the unrestricted results of the MIM-Risk model already fulfills the restrictions that the sensitivities β_{pj} are non-negative and the sum does not exceed unity.[4] In contrast to the unrestricted approach where the residual term has zero mean by construction, the residual of an ACF model contains the mean excess return of the fund portfolio which we extract by subtracting the return generated in-sample by the ACF-model from the empirical return of the fund (e.g., Dietze et al., 2009).

– – (6)

3. Data

3.1 SOURCES, SAMPLE SELECTION, AND PRE-PROCESSING

We obtain data on bond mutual funds from the CRSP survivorship bias-free US mutual fund database (CRSP), Merrill Lynch and Barclays Capital US bond index

[4] As MIM-Risk does not contain R_f as explanatory variable the sensitivities add to less than one if the sensitivity to R_f in ACF-Risk is positive.

data from the Thomson Financial DataStream database, and the risk free rate of return (the 1-month US Treasury bill rate) from the Kenneth R. French online data library.[5]

As of 12/2009, the CRSP database contains 43,668 US based funds. From these we extract the bond funds using Strategic Insight and Lipper objective codes.[6] We include in our analysis all funds that are exclusively classified either as corporate, government, mortgage backed, non-single-state municipal, money market, or general bond funds throughout their existence. In total, we identify 7,964 funds as bond funds, of which 7,940 funds have returns as well as TNA and expense ratio data available in the period from 01/1993 through 12/2009.

Unfortunately, this data is partly incomplete or inconsistent and has to be pre-processed before use. In terms of the fund age we observe that for 14 % of the 7,940 funds the first offer date reported in the CRSP database is inconsistent: i) it is missing, ii) the earliest return observation occurs before the CRSP first offer date, or iii) the CRSP first offer date is reported clearly before the earliest return observation (36 months or more). Therefore, we consistently measure age for all funds as the count of months since its earliest return observation.

In case of the monthly returns we observe that 3 % of the monthly data points are missing, or that 7 % of funds have more than 12 missing monthly return data points, respectively. However, we do not fill the missing values as we majorly use aggregated data. In the cases where we use individual fund observations funds with missing returns are excluded.

In case of the monthly TNA we find that 9 % of the monthly TNA data points are missing or that 11 % of funds have more than 24 missing monthly TNA data points, respectively. As we need complete TNA data for the value-weighting of the monthly returns and for the aggregate size of our fund portfolios we use the three-step-

---

[5] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[6] Strategic Insight objective codes are available from 01/1993 through 09/1998 (CRSP mutual fund database guide, 2010). Lipper objective codes are available from 01/2000 through 12/2009. For the 15 months from 10/1998 through 12/1999 there is no classification scheme available but all funds starting or disappearing during this period are consistently classified before or afterwards, respectively.

procedure used by Rohleder et al. (2010) to fill the missing values. The filled TNA data points account for less than 3.5 % of total TNA.

In case of the expense ratio the data is not available on a monthly basis. Instead, the database provides begin- and end-dates for the time period an expense ratio was applicable for a specific fund. We use this information to fill the months between these dates with the respective expense ratio. If the expense ratio misses in the beginning of a funds life we extrapolate backwards the earliest expense ratio available until the fund start.

Around 79 % of the 7,940 “funds” represent share classes of larger funds while only 21 % are single share class funds. Some multiple share class funds in our sample consist of up to 16 share classes while the majority has between 2 and 7 different share classes. These usually differ in terms of fees and target investor groups (e.g., Morey, 2004; Jones et al., 2005; Evans, 2010) but also with respect to size and age. As size and age are of major importance to our analysis of bond fund disappearance we are primarily interested in the characteristics of the fund rather than the characteristics of separate share classes. Also, if one share class disappears the underlying portfolio/fund still exists and is not to be counted as disappeared (e.g., Zhao, 2005). Therefore, we merge the share classes belonging to the same fund by monthly value-weighting share class returns and share class expense ratios, by monthly accumulating share class TNA, and by applying the age of the oldest share class as the age of the fund. Unfortunately, the information provided by CRSP which share class belongs to which fund is incomplete and available only after 07/2003.[7] Therefore, we identify the share classes of a fund by fund name and CRPS portfolio number referring to Bessler et al. (2010) and obtain 3,431 funds.

For these funds, we calculate monthly fund flows which are not given explicitly by CRSP as the (percentage) change in monthly TNA adjusted by the monthly total return following Brown and Goetzmann (1995). In order to eliminate extreme outliers, e.g. for new funds starting from zero TNA, we cap percentage fund flows at 100 %. The flow to fund *i* in month *t* is given by

[7] CRSP mutual fund database guide (2010).

(7)

and

(8)

Lastly, we observe an implausibly high value for fund starts in 09/2008. This could stem from incorrect data or falsely incorporated new data sources into CRSP. Therefore, we exclude all funds where the time gap between CRSP first offer date and the earliest return observation is more than 36 months, thereby completely solving the problem. Our final fund sample consists of 3,192 US bond mutual funds.

Figure 1 shows how this sample divides into different survivor groups over time. Similar illustrations for asset class sub-samples are displayed by Figure A.1 in the Appendix. Figure 1 shows that the full-sample develops quite steadily over time and that the total number of funds existing at any point in time remains rather stable. A noticeable feature is an abrupt increase in non-survivors (initial and new) around the time the 2007 financial crisis became apparent. From Figure A.1, it can be seen that this is primarily driven by money market funds which show the same feature in exaggerated form such that one can conclude that money market funds were primarily and directly affected by the financial crisis.

[Insert Figure 1 here.]

3.2 SUMMARY STATISTICS

Fund starts and disappearances

To report how fund starts and fund disappearances are distributed over time during our sample period, Table III shows yearly fund starts (Panel I) and fund disappearances (Panel II) in the US bond mutual fund market between 01/1993 and 12/2009 for the full-sample and different asset classes. Panel I shows that fund starts in general decrease over time such that, e.g., in the sub-period from 1993-2001 almost double the number of funds started operations (129.0 p.a.) than in the later sub-period from 2002-2009 (64.9 p.a.). This relation also holds for most of the asset classes except for general bonds where more than 43 % of all fund starts occur during the last 3 years of the sample period (see also Figure A.1 in the Appendix for illustration). In total, 1.680 funds start during the sample period.

[Insert Table III here.]

Panel II of Table III shows that fund disappearances are distributed conversely over time as for the full sample more disappearances occur in the later sub-periods (113.3 p.a. in 2002-2009) than in the earlier sub-periods (89.9 in 1993-2001). This is also the case for most of the asset classes except for government bond funds and mortgage backed bond funds where disappearances occur majorly in the earlier sub-periods. Municipal bond fund disappearances are distributed almost evenly over time. In total, 1,715 funds disappear during our sample period.[8]

As there are more funds disappearing than starting during our sample period and fund starts decrease sharply over time while fund disappearances simultaneously increase, survivorship bias could be a more serious problem today than it was in 1993 given that we find a systematic relationship between disappearance and performance like the one documented for equity funds.

Fund characteristics

To provide a first descriptive overview over the characteristics of the funds in our sample, Panel I of Table IV shows summary statistics for the full-sample in the full period 1993-2009. Of the full-sample of 3,192 US bond mutual funds 1,512 initially existed in 01/1993 and 1,680 entered as new funds afterwards. In 12/2009 a total number of 1,477 end-of-sample survivors remain of which 686 are full-data survivors and 791 are non-full-data survivors. During the sample period 1,715 funds disappear (non-survivors) of which 825 where initial funds and 890 were new funds.

---

[8] Noteworthy is the unusually low value of only 6 fund disappearances in 1999. However, the 12/2009 version of CRSP reports fund end dates in 1999 for only 53 funds (share classes) where the majority is classified as equity mutual funds.

[Insert Table IV here.]

In 12/2009 our sample had a total volume of 4,401,209 Mio US$ of which 65 % were held by full-data survivors and 35 % by non-full-data survivors. Over the full period, full-data survivors with a mean size of 2,278 Mio US$ are nearly double the size as the average fund (1,276 Mio US$) and almost five times larger than an average non-survivor (395 Mio US$) during our sample period. The smallest funds on average are new disappeared funds with 275 Mio US$. For different sub-periods Panels II-V (upon request[9]) show that average fund size grows from earlier to later sub-periods for all fund groups. Also, Panels VI-XI (upon request) show that money market funds are by far the largest funds with an average size of 2,238 Mio US$ followed by mortgage backed funds (1,022 Mio US$), corporate bond funds (683 Mio US$), municipal bond funds (626 Mio US$), and general bond funds (792 Mio US$). Clearly smaller are government bond funds with only 319 Mio US$ on average.

In terms of the expense ratio, Table IV shows an average for the full-sample of 0.7291 % p.a. The highest expense ratio is displayed for non-survivors with 0.7816 % p.a. and especially initial disappeared funds with 0.8022 % p.a. Non-full-data survivors show the lowest expense ratio with only 0.6782 % p.a. on average. Over time, bond fund investment became cheaper such that, e.g., during the 2001-2009 sub-period an average fund had an expense ratio of 0.7056 % p.a. Comparing different asset classes reveals that money market funds have by far the lowest expense ratio with only 0.5622 % p.a. while general bond funds show an extremely high expense ratio of 1.3204 % p.a. Between these extremes the expense ratios are quite close at 0.7895 % p.a. for municipal bonds funds and 0.8245 % p.a. for mortgage backed bond funds.

A look at the net excess returns of different survivor and non-survivor portfolios shows that non-survivors under-perform survivors. This is especially pronounced

---

[9] In addition to the full-sample in the period from 01/1993 through 12/2009, we conduct all our empirical summary statistics and empirical analyses in 4 different sub-periods and for 6 different asset classes (see Table A.1 in the Appendix for details). This means that each table in this paper exists in up to 11 versions. Due to space limitations we present only the tables reporting results for the full-sample in the full-period. The remaining results are available from the authors upon request.

between non-full-data survivors, which show the highest average return of 0.1151 % p.m., and initial disappeared funds, which show the lowest average return of 0.0268 % p.m. The differences are, however, not as dramatic as for equity funds (e.g., Carhart, 2002; Rohleder et al., 2011).

Over time, returns on average increase and become more volatile, leading to a monthly net excess return of 0.1015 % p.a. in the period from 2002-2009 with a standard deviation of (1.34 % p.m.) while in the 1993-2001 the average net excess return is 0.0356 % p.a. with a standard deviation of (1.01 % p.a.). The rise in volatility also leads to increased return differences in the latter periods. In case of the extreme sub-groups we observe even negative net excess returns for new disappeared funds of -0.0279 % p.a. during the 2002-2009 sub-period while non-full-data-survivors earn 0.1495 % p.a. during the same period. Return differences and volatility are even higher in the sub-period from 2007-2009 where the standard deviation of the net excess return for the unbiased portfolio is 1.89 % p.m. The maximum net excess return difference between non-full-data survivors and new disappeared funds is 0.6514 % p.m. (8.1 % p.a.). This confirms our argument that the variability of fund returns increases over time with a growing number of bond funds available and more competition between these funds.

We find distinct differences between different styles. Corporate, mortgage backed, and general bond funds show very high net excess returns of up to 0.1522 % p.m. (general bond) while money market funds severely under-perform and show even negative net excess returns of -0.0292 % p.m. Government and municipal bond funds show medium net excess returns of 0.1066 % p.m. and 0.0859 % p.m., respectively. Apart from that, the relations between the sub-groups also hold for the different asset classes with only little variation.

Lastly, looking at percentage fund flows Table IV shows that new funds with 2.36 % p.m. grew faster than the full-sample with 1.11 % p.m. while initial funds grew very moderately with only 0.34 % p.m. The fastest growing funds are non-full-data survivors with 2.80 % p.m., the slowest growing group are initial disappeared funds with only 0.05 % p.m. In absolute terms non-full-data survivors grew by

14.92 Mio US$ p.m. while initial disappeared funds even decreased by 1.04 Mio US$ p.m.

Looking at different sub-periods shows higher absolute flows in later periods while percentage flows decreased due to higher average size. Also, we observe higher volatility of flows in later periods and larger differences such that initial disappeared funds show high absolute outflows of 4.06 Mio US$ p.m. while especially non-full-data survivors experience extreme inflows of, e.g., 24.63 Mio US$ p.m. during the sub-period from 2002-2009. The relations between the sub-groups remain the same as in the full period.

The same applies for different asset classes. We observe the highest absolute inflows into corporate (4.37 Mio US$ p.m.), general (3.88 Mio US$ p.m.), and especially into money market funds (13.49 Mio US$ p.m.). The opposite extreme is represented by mortgage backed bond funds for which we document outflows of 2.56 Mio US$ p.m., supposedly due to the sub-prime crisis. Initial disappeared mortgage backed funds experienced outflows of 47.99 Mio US$ p.m.

Hypotheses

From these statistics on the characteristics on several different US bond mutual fund groups we can draw hypotheses for our empirical analysis:

H1) For the full-sample we expect fund disappearance to be significantly correlated to returns because survivors clearly out-perform non-survivors. We also expect this relation to be pronounced for specific asset classes.

H2) We expect fund disappearance to be highly correlated with fund size as non-survivors are distinctly smaller on average than survivors such that smaller funds are more likely to disappear.

H3) As non-survivors show the highest expense ratios we expect fund disappearance to be systematically related to expense ratio such that funds with a higher expense ratio are more likely to disappear.

H4) We expect fund flow to be systematically related to fund disappearance as flows to non-survivors are distinctly smaller than flows to end-of-sample survivors such that funds with smaller positive flows or even outflows are more likely to disappear.

H5) If H1 holds, we expect to find economically significant survivorship bias in the performance of US bond mutual funds. Again, we expect survivorship bias to be of special importance for specific asset classes.

4. Empirical Results

4.1 DISAPPEARANCE OF BOND MUTUAL FUNDS

To analyze the disappearance of bond mutual funds we use probit models like in Brown and Goetzmann (1995) and Rohleder et al. (2010) plus additional model specifications using single characteristics to assess their explanatory power.[10] The results are presented in Table V where Panel I shows multiple characteristics models for all styles in the period from 01/1993 through 12/2009 and Panel II shows the respective single characteristics models.

In terms of relative fund returns, models 1 and 3 show that returns lagged 1 year have a negative impact on disappearance such that successful funds are less likely to disappear. Model 2 incorporates the return of the last 5 years in order to assess whether return measures over longer periods have significantly higher explanatory power. The log-likelihood based Nagelkerke R^2 and Pseudo R^2 statistics document that this is not the case. In the remaining models the negative relation between return and disappearance holds only for small funds. These show negative and significant coefficients while the coefficients on the general factor are positive and insignificant and the coefficients on large funds are unsystematic. In models 5, 7, and 8 we add returns lagged 2 and 3 years, respectively, in order to assess whether returns influence disappearance over longer horizons. The results show significant and negative impact

[10] As the correlations between the characteristics are shown to be relatively low for the majority of characteristics combinations (see Table I), this should allow an approximate comparison of their explanatory power.

on disappearance while the interaction with small and large dummies shows no significant effects. Looking at Panel II, however, shows that the explanatory power of relative returns in general is very low with Nagelkerke R^2 statistics of 0.95 % and 0.56 % and even smaller Pseudo R^2 statistics of 0.31 % and 0.17 %. This means that the impact of returns is negligible. Therefore, we cannot confirm H1.

[Insert Table V here.]

Fund size shows significant and negative impact on disappearance such that larger funds are less likely to disappear. From models 1 and 2 we use relative size and find significant and negative coefficients. The explanatory power is high with a Nagelkerke R^2 statistic of 3.54 % documented in Panel II. In model 3 we use log size causing the R^2 statistics to rise significantly and the intercept to be distinctly less negative.[11] Also, Panel II shows that log size explains disappearance much better than relative size with a Nagelkerke R^2 statistic of 11.56 %. Therefore, we use log size in all remaining multiple characteristics models and show that the impact of size is consistently negative and highly significant. These results confirm H2 that fund size is the predominant factor for explaining bond fund disappearance.

In terms of the fund age we find significant and negative impact on disappearance in models 1 and 2 but unsystematic and partly insignificant impact in the remaining multiple characteristics models. This could be due to age showing higher correlation with log size (30.23 %, see Table I) than with relative size (11.43 %), such that log size already partly accounts for an older age in models 3 through 8. The explanatory power of age alone is relatively low with a Nagelkerke R^2 statistic of 1.02 %, but still larger than that of relative returns.

In terms of the expense ratio we find large positive and highly significant coefficients in models 1 and 2 such that funds with higher expense ratios are more likely to disappear. The explanatory power of the expense ratio shown in Panel II is higher than that for returns and age with a Nagelkerke R^2 statistic of 1.65 %. This confirms

[11] In further models we also use “relative log size” which yields results very similar to log size such that we do not report these models in the paper.

H3. In the remaining multiple characteristics models the coefficients are smaller but still positive and partly significant which could be due to expense ratios showing higher correlations with log size (-34.53 %, see Table I) than with relative size (-18.47 %). This means that log size partly accounts for expense ratios already.

In models 5, 6, and 8 of Panel I we incorporate the relative flow to the fund and find that fund flow lagged 1 year shows a negative and highly significant relationship to disappearance such that funds with high inflows are less likely to disappear. Also, Panel II shows that the explanatory power of fund flows is very high with Nagelkerke R^2 statistics of 5.77 % and 6.51 %, respectively. The impact of fund flows in t-2y is not significantly different from zero while fund flows in t-3y show again negative and partly significant coefficients. For interaction terms with small and large dummies we find that high flows to large funds have no significant influence while high flows to small funds increase the probability of disappearance. This last and a bit surprising finding could again be due to the correlation of Small : Flow (t-1y) to log size of 27.65 % (see Table I) as Panel II shows that flows to small funds alone significantly decreases the probability of disappearance. These findings confirm H4 that funds with higher inflows are less likely to disappear. However, as our analysis makes no statement about causality, it is not clear whether outflows cause disappearance or foreseeable disappearance causes outflows. We further investigate this later.

The results for the different sub-periods are presented in Panels III-X of Table V (upon request). These show that over time the influence of the different characteristics is quite stable. This is particularly true in terms of fund size, fund age, and fund flows as these show very similar influence and of explanatory power in all sub-periods. Also similar but with higher significance and higher explanatory power in the earlier sub-periods are the results for fund expense ratios which could be due to expense ratios decreasing over time as shown in Table IV. The influence of returns is also similar in most sub-periods but, as an exception, the influence is higher during the sub-period covering the financial crisis from 2007 through 2009. However, even during this sub-period the explanatory power of size and flows is distinctly higher than that of returns.

Analogously, the results for different asset classes (upon request, Panels XI through XXII) show similar relations. Size is the dominant factor with (very) high explanatory power and consistently negative and significant influence on the disappearance of bond funds from all asset classes. To a certain degree, the same applies to age, expense ratio, and fund flows. For age and expense ratio the influence is similar except for money market funds where we find less significant coefficients and lower explanatory power. In case of fund flows we find that the relation to fund disappearance is exceptionally strong for money market funds and mortgage backed bond funds while it is comparatively weak for government bond funds.

For returns, the results are more differentiated. Consistent with H1 we find negative and significant coefficients as well as above average explanatory power for corporate (Nagelkerke R^2: up to 2.87 %), municipal (2.86 %), mortgage backed (6.52 %), and general bond funds (8.33 %).[12] The second part of H1 can therefore be confirmed. For government bond funds and money market funds on the other hand, the explanatory power of relative returns is very low and the coefficients are majorly insignificant.

In a nutshell: In contrast to equity funds where returns play a major role in the disappearance of mutual funds we cannot find this relation for bond funds. Here, the relationship is almost negligible, except for certain asset classes like corporate and municipal bond funds. Further, we identify the size of funds to be the dominant factor for bond fund disappearance such that larger funds are more likely to disappear. Flows play another major role in that higher flows decrease the odds of disappearance. To get a more detailed view on the economics behind these findings we analyze in the sections to come the performance of differently constructed fund portfolios.

4.2 PERFORMANCE AND SURVIVORSHIP BIAS

Table VI shows different performance measures for the full sample and for survivor/non-survivor and initial/new sub-groups (see Figure 1 and Table III) in the period from 01/1993 through 12/2009. The measures we use are the mean net excess return (MER), linear single-index (SIM) and multi-index models (MIM) following

[12] Note that the Nagelkerke R^2 statistics of all multiple characteristics models for mortgage backed (up to 34.46 %) and general bond funds (up to 40.57 %) are already very high compared to other asset classes such that these values might not be directly comparable.

Blake et al. (1993), and a non-linear asset-class-factor model (ACF) following Sharpe (1988, 1992).

Panel I reports performance measures, factor loadings, and R^2 statistics for equal-weighted fund portfolios showing that non-survivors, especially new disappeared funds, perform worst for all performance measures. On the other hand, end-of-sample survivors, especially non-full-data survivors, perform best for all performance measures. The MER is positive for all sub-groups, but especially for non-survivor groups the measures are not significantly different from zero. Moreover, for none of the sub-groups do we find positive risk-adjusted performance measures such that bond mutual funds are, on average, not able to add value for investors on a risk-adjusted basis. In magnitude, the performance results closely correspond to the results by, e.g., Ferson et al. (2006) and Chen et al. (2010).

[Insert Table VI here.]

Looking at the different performance models shows that the under-performance of the fund groups gets more serious the more factors we use to explain excess returns, such that the SIM shows negative but partly insignificant under-performance while the MIM-Maturity model shows consistently significant under-performance for all sub-groups. Further, looking at the R^2 statistics we find that the SIM yields a distinctly inferior fit compared to the MIM and ACF measures. This could be because the broad Barcleys Capital US Aggregate Bond index does not include municipal bond and high yield bond components.[13] The MIM and ACF models, which explicitly incorporate components for different asset classes show no substantially differences in their R^2 statistics.

Panel II of Table VI shows results for the value-weighted portfolios. Again, non-survivors show the lowest performance while survivors, especially non-full-data survivors, show the highest. Further, new funds on average outperform initial funds. But, the differences between the sub-groups are smaller compared to the equal-weighted results. Moreover, non-full-data survivors show positive but insignificant

[13] https://ecommerce.barcap.com/indices/index.dxml, Factsheets.

alphas for all risk-adjusted measures. Comparing equal-weighted and value-weighted results shows that the MER measures are higher when equal-weighted, suggesting that smaller funds earn higher total returns. In contrast, all alphas are higher when value-weighted, suggesting that larger funds earn higher risk-adjusted returns. To assess this further in more detail, we conduct a size-decile analysis in a later section.

Also of interest are the factor loadings of the sub-groups. The ACF-Risk loadings for the equal-weighted full-sample show that a very high percentage of the excess return is explained by the risk free return which is certainly due to the large number of money market funds in the sample. Panel II confirms this suggestion as the loadings on R_f are even higher because money market funds are very large on average (see Table III). Among the other factors, another emphasis is on the municipal index while the loadings on the remaining indices are more or less even.

Table VI enables a comparison between the loadings on the MIM-Risk and the ACF-Risk models.[14] Both models use the same explanatory variables such that the loadings are identical if the restrictions of the ACF model also hold for the MIM model. This is the case for most of the sub-groups in Panel I, except for non-survivors and new disappeared funds. Here, the MIM-Risk loadings on the mortgage backed index are negative and become zero in the restricted case. In theory, the negative loading is interpreted as a short position in mortgage backed bonds which is not allowed for legal reasons. However, an alternative interpretation could be that another index, namely the government bond index, implicitly carries mortgage backed features (e.g., government guaranteed FNMA[15]) and over-accounts for mortgage backed bond influences on non-survivors. In this case a negative coefficient on the mortgage backed index acts as compensation. Evidence in favor of this interpretation could be drawn from relatively high factor loadings on the government index for the respective

---

[14] Due to space limitations in the table, the loadings for the MIM-Risk model are not displayed in the paper but available from the authors upon request. Briefly, wherever an ACF factor loading is zero with a p-value of 100 % the respective MIM factor loading is negative. Also, the severity of the violation of the restriction can be derived from the difference between the Pseudo R^2 statistics and between the alphas of both models.

[15] Federal National Mortgage Association.

non-survivor groups and relatively high correlation between both indices (82.69 %, see Table II). Moreover, the Pseudo R^2 differences between the models are quite small such that the violation is not very severe. In Panel II it is again the non-survivor sub-groups for which the loadings on the corporate bond index are negative in the unrestricted model and zero in the restricted model. Here, the same alternative interpretation applies to the corporate bond index and the high yield bond index, as the correlation between both indices is also relatively high (67.46 %, see Table II). Therefore, the use of the ACF model in order to account for legal restrictions could be counterproductive as long as the indices are correlated and therefore not entirely selective (e.g., Chen et al., 2010).

As Table VI shows out-performance of survivors over non-survivors for both weighting schemes, Panel I of Table VII displays survivorship bias results and differences between different survivorship bias results. We find that there is significant and positive survivorship bias in the bond mutual fund market for all performance measures. For end-of-sample survivorship bias, the equal-weighted results are between 0.0149 and 0.0164 % p.m. (0.18 - 0.20 % p.a.) and for full-data survivors between 0.0048 and 0.0151 % p.m. (0.06 - 0.18 % p.a.). These values are very small compared to the results for the equity mutual fund market documented by various studies (e.g., 1.50 % p.a. in Malkiel, 1995; 0.96 % p.a. in Carhart et al., 2002; 1.57 % p.a. in Rohleder et al., 2010). However, the relative survivorship bias, which sets the absolute figure in relation to the unbiased performance, is quite high with approximately 40 % for SIM and around 25 % for the other models. This clearly is of economic relevance, especially when considering that the main difference between survivors and non-survivors is due to differences in the expense ratios (Table IV). This contradicts our expectation 5). Value-weighted survivorship bias results on general are smaller with results for the end-of-sample survivors between 0.0040 and 0.0050 % p.m. (0.05 - 0.06 % p.a.) and for the full-data survivors between 0.0026 and 0.0065 % p.m. (0.03 - 0.08 % p.a.), because non-survivors are smaller than survivors.

[Insert Table VII here.]

Concerning survivorship bias differences we find that the differences between different survivor definitions are not significantly different from zero. An exception is the difference between the equal-weighted MER measures which is significant on the 5 %-level but economically of no importance with 0.01 % p.m. (0.12 % p.a.). In the case of the differences between equal-weighted and value-weighted results, we find statistically significant and positive results in most cases with a maximum difference of 0.0117 % p.m. (0.14 % p.a.).

The panels III-X of Table VI (upon request) show performance in different sub-periods. The results show that the general performance is lower in the earlier periods and higher in the later periods such that we observe the highest performance during the financial crisis from 01/2007 through 12/2009. Also, the performance differences between survivors and non-survivors are higher in latter periods such that survivorship bias (upon request, Table VII, Panels II-V) is mostly higher in the later periods with a maximum SIM survivorship bias of 0.26 % p.a. (0.0219 % p.m.) for full-data in 1993-2001 and a corresponding relative survivorship bias of 167.18 %.[16] This confirms the first part of our expectation 5.a.

Also of interest is the performance of bond funds from different asset classes which we display in Panels XI through XXII of Table VI (upon request). The highest performance show corporate and mortgage backed bond funds while money market funds show very low performance.[17] Money market, municipal, and government bond funds on the other hand show low performance. General bond funds show very high MER but very low alphas suggesting that these take disproportionally high risk.

---

[16] Note that the survivor/non-survivor and new/initial sub-groups are sub-period specific such that a fund identified as survivor (new) in an earlier period can be identified as a non-survivor (initial) in a latter period. Therefore, the sub-periods are not directly comparable and serve as an approximation. Also, survivorship bias depends on the length of the time periods as, on average, fewer funds disappear during a shorter period such that the end-of-sample survivors and the unbiased sample are very much alike.

[17] Actually, money market funds show the highest alphas. But, with a maximum R^2 statistic of 10 % one cannot seriously speak of risk-adjusted performance in the case of money market funds.

Exploring the factor loadings (ACF) for the asset classes shows that corporate bond funds bear influences from all indices, with the exception that the loadings on municipal and mortgage indices are zero for very few sub-groups. Government bond funds also show influences from all indices except for the municipal factor. The same applies to mortgage backed funds, especially for the value-weighted portfolios. For municipal bond funds the influences are much clearer because the loadings on government, corporate, and mortgage backed are zero for almost all sub-groups. Also, money market funds show a very clear picture as the loading on the risk-free rate of return is consistently higher than 99 % plus negligible loadings on mortgage backed and very seldom on high yield.

Very interestingly, the dominant influence on “general bond” is the high yield index. In addition, we even observe zero loadings on R_f for non-full-data survivors. This suggests that, instead of representing the bond market in “general” these bonds take exceptionally high risk which explains why general bond funds show the highest MER but very low alphas.

Panels VI-XI of Table VII show survivorship bias estimates for different asset classes. We find the highest SIM survivorship bias for general bond funds with up to 0.52 % p.a. (0.0430 % p.m.) and for corporate bond funds with up to 0.37 % p.a. (0.0306 % p.m.). These figures correspond to relative survivorship bias estimates of 417.48 % and 93.58 %. Money market funds consistently show the lowest survivorship bias with up to 0.0034 % p.m. (0.04 % p.a.). This confirms the second part of our expectation 5.a.). Mortgage backed funds, however, show negative survivorship bias for all MIM and ACF measures such that fund performance is understated by survivorship bias which is controversial to research claiming that their anyway negative results are economically not harmed by the bias (e.g., Detzler, 1999).

In a nutshell: Despite the large number of non-survivors and the length of the sample period, absolute survivorship bias is very small. However, in relation to the unbiased performance, survivorship bias seriously overstates performance, especially in later sub-periods and in certain asset classes. In terms of performance, corporate and mortgage backed bond funds show the highest MER and alpha measures while money market funds show the lowest performance.

4.3 PERFORMANCE OF SIZE-DECILE PORTFOLIOS

The probit analysis of fund disappearance documents that the fund characteristic with the highest explanatory power is the size of a fund. Therefore, we now analyze the performance and the disappearance rates of bond funds in more detail by applying a size-quantile approach in reference to Chen et al. (2004) and Rohleder et al. (2010). Therefore we construct size-decile portfolios for which we calculate MER, SIM, and MIM performance measures as above.[18]

Panel I of Table VIII shows the size-decile results for full-sample in the full period. Decile 10 represents the largest 10 % of funds. With an average size of 9,067 Mio US$, these are on average more than 1,000 times larger than the smallest 10 % of funds in decile 1 with only 8 Mio US$.

[Insert Table VIII here.]

Concerning the performance of equal-weighted and value-weighted size-decile portfolios, Table VIII shows twofold results for MER and the risk-adjusted measures. In terms of the MER the relatively small funds in decile 3 show the highest performance. The worst performance is displayed for decile 10 and thereby for the largest funds. In terms of risk-adjusted performance decile 10 consistently shows the highest alpha for all SIM and MIM measures while decile 1 of the smallest funds consistently shows the worst risk-adjusted performance. This closely corresponds to our former performance results where the MER is higher for equal-weighted portfolios and the alphas are higher for value-weighted portfolios. The reason could be that the largest funds with the lowest returns take by far the lowest risk such that

[18] Note that we do not continue to use the ACF model for different reasons. The first reason is that there is no differences between MIM-Risk and ACF-Risk for the unbiased sample in Table VI, such that the violations are supposedly small. Further, an alternative interpretation of the violations could be that the indices are not selective enough and negative loadings act as compensation. Moreover, in the following sections we use differences between portfolios rather than portfolio returns such that the restrictions do not apply.

risk-adjusted performance is relatively high. This is a distinct feature we observe for money market funds which are the largest asset class in our sample and might therefore drive the results.[FN?]

The last three columns of Table VIII display disappearance rates for the size-deciles in reference to Rohleder et al. (2010). These represent the odds of fund disappearance at any point in time dependent on the allocation to a certain size-decile. The results show that the largest funds are least likely to disappear while the smallest funds show the highest disappearance rate. This confirms and emphasizes the results from the probit analysis.

The panels II-V of Table VIII (upon request) show size-decile results in different sub-periods documenting that fund size in general grew over time such that funds are largest during the sub-period from 2007-2009. Also, the table documents higher performance in the later sub-periods. The relations between the size-decile portfolios, however, remain stable such that larger funds show significantly higher alphas than smaller funds in all sub-periods. Moreover, the sub-periods yield similar results for disappearance rates.

The results on the full-sample might be driven by different asset classes, which are not evenly distributed among the size-deciles due to significantly different average size. Therefore, panels VI-XI of Table VIII (upon request) show results for different asset classes. For most asset classes we document the worst performance for the smallest funds, whereas the largest funds not always perform best. For some asset classes and depending on the performance measure it is also the medium size deciles which show the highest performance, e.g. corporate in case of the MIM measures, government (MIM-Maturity), and municipal bond funds (SIM, MIM-Risk). The largest money market funds consistently and significantly out-perform all other deciles while the largest general bond funds out-perform without statistical significance. A striking exception to this rule is represented by mortgage backed funds which show the opposite relation. Here, decile 9 (2nd-largest) performs worst while decile 3 (equal-weighted, MIM) and decile 1 (value-weighted, SIM and MIM) perform best such that larger funds under-perform smaller funds. This closely corresponds to the negative survivorship bias we find in the former section. The results for disappearance rates from different asset classes show no difference to the results for the full-sample such that larger funds are less likely to disappear.

In a nutshell: The relation between performance and size depends on the measures and is different for different asset classes. While the smallest funds show the highest MER it is the largest size-decile which shows the highest alphas. This holds for all sub-periods and for most asset classes except for mortgage backed funds where we document the opposite relation. In terms of the disappearance of funds, the largest funds are least likely to disappear while the odds of disappearance rise almost monotonically with decreasing size, independent from asset class or sub-period.

4.4 NON-SURVIVORS VS. SURVIVORS

In our probit analysis we find returns to be economically almost unrelated to disappearance. This holds for various lagged return variables. In our performance analysis we find that survivorship bias is very small but statistically significant anc economically relevant. In addition, we find that outflows are related to disappearance but we are not sure about causality. Therefore, we analyze in this sub-section the size of non-survivors and performance differences between non-survivors, sub-divided into liquidated and merged funds, and end-of-sample survivors (e.g. Blake and Timmermann, 1998) in different time frames before disappearance.

Panel I of Table IX shows the performance difference and size for 1,445 non-survivors from all styles in the time period from 01/1993 through 12/2005. Non-survivors consistently under-perform the end-of-sample survivors in the full-period by up to 0.55 % p.a. (equal-weighed, SIM) as well as in the different time frames before disappearance. Both equal- and value-weighted non-survivor portfolios show the highest under-performance in the second to last year of existence with up to 0.92 % p.a. (equal-weighted, MIM-Risk). The results for the best performance (smallest under-performance) is very different for equal- and value-weighted portfolios as the best equal-weighted performance is more than 4 years before disappearance while value-weighted non-survivors perform best in their last year of existence. In terms of size, non-survivors decrease constantly over time such that they are smallest during their last year. Therefore, significant outflows start already more than 4 years before fund disappearance such that outflows trigger disappearance rather than the other way round.

[Insert Table IX here.]

Panel II of Table IX shows analogue results for 593 liquidated funds. These under-perform the end-of-sample survivors in the full period as well as in most time frames before disappearance. Equal-weighted there is hardly any difference to non-survivors in general except for the last year, where liquidated funds show the worst under-performance. Value-weighted, there are distinct differences as here liquidated funds perform best and even out-perform survivors in the “Higher than 4th” timeframe while they consistently and significantly under-perform during their last 4 years of existence. In terms of size we find very interesting results as liquidated funds are clearly larger than merged funds in the full period but decrease faster and are therefore very small when disappearing.

Panel III shows results for 852 merged funds. Equal-weighted, there is again no difference between liquidated and merged funds except for the worst performance in the second to last year and moderate under-performance in the last. Value-weighted, however, there are differences such that merged funds under-perform liquidated funds in the full-period. Interestingly, merged funds show their best performance in the last year. In terms of size, merged funds are on average smaller but decrease very slowly and are over 100 Mio US$ larger in their last year than liquidated funds. This explains why non-survivors in general show their best value-weighted performance in the last year because merged funds are distinctly larger and exist in larger numbers than liquidated funds.

The Panels IV-IX of Table IX (upon request) show results for different sub-periods (1993-2001 and 2002-2005). These closely resemble the above described relations, especially in the earlier sub-period. In the later sub-period we find that non-survivors show their best performance in earlier time frames and their worst performance in time frames close to disappearance for both liquidated and merged funds.

For different asset classes the Panels X-XXVII (upon request) also show relations very similar to the full-sample results for most of the asset classes. However, mortgage backed funds out-perform end-of-sample survivors in most of the time frames, especially on a risk-adjusted basis, which confirms our survivorship bias results. This is particularly true for liquidated funds which out-perform in all time-frames except for the 3rd year before disappearance. In contrast, merged funds under-perform in most periods except in the 3rd year before disappearance. Also, liquidated funds decrease dramatically from 2,449 Mio US$ to only 25 Mio US$ within the last 5 years while merged funds decrease from only 354 Mio US$ to 185 Mio US$. These very special findings suggest that the decision to close the fund is not influenced by performance but by fund size and significant outflows.

In a nutshell: These findings suggest that the decision to close a fund is only partly influenced by performance. But, as the performance differences are very small compared to the results documented for the equity fund market, the relation is very weak. In contrast, the influence of size and flows plays a very important role for fund disappearance. Also, the decision whether to liquidate or merge also depends mainly on the size and the outflows of a fund. This also holds for the sub-periods and for most asset classes except mortgage backed bond funds.

5. Conclusion

In Blake et al. (1993) the authors state that survivorship bias is of minor importance to bond funds as bond fund returns are not very variable and fewer funds disappear. Following research often refers to that statement not further investigating disappearance or survivorship bias in bond fund performance. However, times change and today there are a large number of bond funds competing for investors thereby increasing variability in returns and the number of disappeared funds. In addition, the authors use biased samples to estimate the bias. Therefore, we consider it necessary to analyze the disappearance of bond funds and survivorship bias in detail based upon a comprehensive database thereby filling this gap in the literature.

We find that returns have almost nothing to do with the disappearance of bond funds. We find some evidence that returns play a minor role for disappearance of small funds but their explanatory power is negligible. However, we find statistically significant survivorship bias which we consider economically relevant, especially in relation to the unbiased performance as survivorship bias overstates performance by up to 40 % for the full sample. The problem of survivorship bias is even more serious in the later sub-periods and for certain asset classes, where overstatement can be higher than 100 % of the unbiased performance. Also, we find negative survivorship bias for mortgage backed bond funds.

The major influence on disappearance of bond funds is fund size such that larger funds survive while smaller funds disappear. Another important role play fund flows such that funds with higher inflows survive while funds with outflows disappear. Lastly, funds with higher expenses disappear while low-expense funds survive.

Appendix

Table A.1. Fund groups of the fund performance analysis

	Unbiased sample	Non-survivors	End-of-sample survivors	Full-data survivors	Non-full-data survivors	Initial funds	New funds	Initial disapp. funds	New disapp. funds
All styles	1993-2009 1993-2006 / 2007-2009 1993-2001 / 2002-2009								
Corporate Government Mortgage backed Municipal Money market General bond	1993-2009								

Table A.2. Performance models

Model	Variable	Index
SIM	Broad	Barclays Capital US Aggregate Bond
MIM-Risk	Government	Barclays Capital US Aggregate Government
	Corporate	Barclays Capital US Corporate Investment Grade
	Municipal	Barclays Capital US Municipal Bond Index
	High yield	Barclays Capital US High Yield Composite
	Mortgage backed	Barclays Capital US Mortgage Backed
MIM-Maturity	Government intermediate	50 % Merrill Lynch US Agencies 3-5Y + 50 % Merrill Lynch US Agencies 5-7Y
	Government long-term	1/3 Merrill Lynch US Agencies 7-10Y + 1/3 Merrill Lynch US Agencies 10-15Y + 1/3 Merrill Lynch US Agencies 15Y+
	Corporate intermediate	Barclays Capital US Corporate Intermediate
	Corporate long-term	Barclays Capital US Corporate Long
	Municipal	Barclays Capital US Municipal Bond
	High yield	Barclays Capital US High Yield Composite
	Mortgage backed	Barclays Capital US Mortgage Backed
ACF-Risk	Government	Barclays Capital US Aggregate Government
	Corporate	Barclays Capital US Corporate Investment Grade
	Municipal	Barclays Capital US Municipal Bond
	High yield	Barclays Capital US High Yield Composite
	Mortgage backed	Barclays Capital US Mortgage Backed
	Risk free return	1-month US Treasury Bill rate

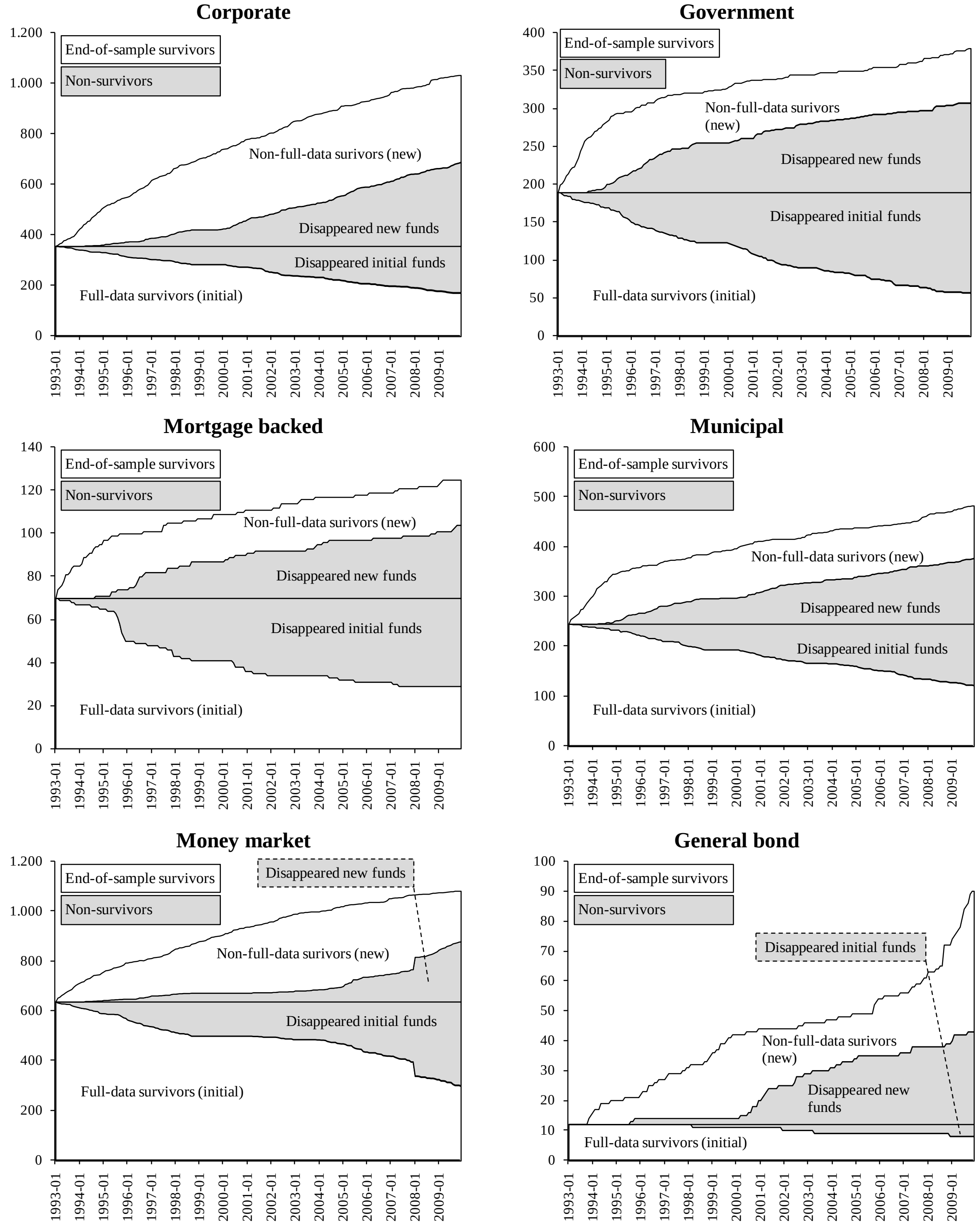

Figure A.1. Sample development for asset classes1993-2009

This figure shows how the asset class sub-samples of our full sample (Figure 1) develop during the sample period from 01/1993 through 12/2009. Note that the sub-figures are scaled differently as the sub-samples obviously differ in the number of funds. Of the total number of 3,192 US bond funds, 1,031 are corporate bond funds, 380 are government bond funds, 125 are mortgage backed bond funds, 484 are non-single state municipal bond funds, 1,088 are money market funds, and 90 are general bond funds.

References

Bessler, W., Blake, D., Lückoff, P., and Tonks, I. (2010) Why does mutual fund performance not persist? The impact and interaction of fund flows and manager changes. Unpublished working paper PI-1009, Justus-Liebig-University Giessen, Cass Business School London, and University of Exeter.

Blake, C. R., Elton, E. J., and Gruber, M. J., The performance of bond mutual funds. *Journal of Business* **66**, 371-403.

Blake, D. and Timmermann, A. (1998) Mutual fund performance: evidence from the UK. *European Finance Review* **2**, 57-77.

Boney, V. and Comer, G. (2010) Are reported mutual fund yields usefull? An analysis of municipal bond funds. Unpublished working paper, University of Denver, Georgetown University.

Brown, S. J., Goetzmann, W. N., Ibbotson, R. G., and Ross, S. A. (1992) Survivorship bias in performance studies. *Review of Financial Studies* **5**, 553-580.

Brown, S. J. and Goetzmann, W. N. (1995) Performance persistence. *Journal of Finance* **50**, 679-698.

Carhart, M. M. (1997) On persistence in mutual fund performance. *Journal of Finance* **52**, 57-82.

Carhart, M. M., Carpenter, J. N., Lynch, A. W., and Musto, D. K. (2002) Mutual fund survivorship. *Review of Financial Studies* **15**, 1439-1463.

Chen, J., Hong, H., Huang, M, and Kubik, J. D. (2004) Does fund size erode mutual fund performance? The role of liquidity and organization. *American Economic Review* **94**, 1276-1302.

Chen, Y., Ferson, W., Peters, H. (2010) Measuring the timing ability and performance of bond mutual funds. *Journal of Financial Economics* (forthcoming).

Cici, G. and Gibson, S. (2010) The performance of corporate-bond mutual funds: evidence based on security-level holdings. Unpublished working paper, Mason School of Business, College of William & Mary, Williamsburg.

Cornell, B. and Green, K. (1991) The investment performance of low-grade bond funds. *Journal of Finance* **46**, 26-48.

Deaves, R. (2004) Data-conditioning biases, performance, persistence and flows: the case of Canadian equity funds. *Journal of Banking & Finance* **28**, 673-694.

Detzler, M. L. (1999) The performance of global bond mutual funds. *Journal of Banking & Finance* **23**, 1195-1217.

Dietze, L. H., Entrop, O., and Wilkens, M. (2009) The performance of investment grade corporate bond funds: evidence from the european market. *European Journal of Finance* **15**, 191-209.

Droms, W. G. and Walker, D. A. (2006) Performance persistence of fixed income mutual funds. *Journal of Economics and Finance* **30**, 347-355

Elton, E. J, Gruber, M. J., and Blake, C. R. (1995) Fundamental economic variables, expected returns, and bond fund performance. *Journal of Finance* **50**, 1229-1256.

Elton, E. J, Gruber, M. J., and Blake, C. R. (1996) Survivorship bias and mutual fund performance. *Review of Financial Studies* **9**, 1097-1120.

Ferson, W., Henry, T. R., and Kisgen, D. J. (2006) Evaluating government bond fund performance with stochastic discount factors. *Review of financial Studies* **19**, 423-455.

Ghallager, D. R. and Jarnecic, E. (2002) The performance of active Australian bond funds. *Australian Journal of Management* **27**, 163-185.

Huij, J. and Derwall, J. (2008) “Hot hands” in bond funds. *Journal of Banking & Finance* **32**, 559-572.

Jensen, M. C. (1968) The performance of mutual funds in the period 1945-1964. *Journal of Finance* **23**, 389-416.

Jones, M. A., Lesseig, V. P., and Smythe, T. I. (2005) Financial advisors and multiple share class mutual funds. Financial Services Review 14, 1-20.

Kihn, J. (1996) The financial performance of low-grade municipal bond funds. *Financial Management* **25**, 52-73.

Malkiel, B. G. (1995) Returns from investing in equity mutual funds 1971 to 1991. *Journal of Finance* **50**, 549-572.

Morey, M. R. (2004) Multiple-share classes and mutual fund composition. Financial Services Review 13, 33-56.

Newey, W. K. and West, K. D. (1987) A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* **55**, 703-708.

Philpot, J., Hearth, D., Rimbley, J., and Schulman, C. T. (1998) Active management, fund size, and bond mutual fund returns. *Financial Review* **33**, 115-126.

Philpot, J., Hearth, D., and Rimbley, J. (2000) Performance persistence and management skill in nonconventional bond mutual funds. *Financial Services Review* **9**, 247-258.

Polwitoon, S. and Tawatnuntachai, O. (2006) Diversification benefits and persistence of US-based global bond funds. *Journal of Banking & Finance* **30**, 2767-2786.

Redman, A. L. and Gullet, N. S. (2007) Impact of fund, management and market characteristics on bond mutual fund performance. *Journal of Asset Management* **7**, 429-442.

Rohleder, M., Scholz, H., and Wilkens, M. (2010) Survivorship bias and mutual fund performance: significance, relevance, and methodical differences. Review of Finance (forthcoming).

Scholz, H. and Schnusenberg, O. (2009) Ranking of equity mutual funds: the bias in using survivorship bias-free datasets. Unpublished working paper, University of Erlangen-Nürnberg and University of North Florida.

Sharpe, W. F. (1966) Mutual fund performance. *Journal of Business* **39**, 119-138.

Sharpe, W. F. (1988) Determining a fund’s effective asset mix. *Investment Management Review* **Nov./Dec.**, 59-69.

Sharpe, W. F. (1992) Asset allocation: management style and performance measurement. *Journal of Portfolio Management* **18**, 7-19.

Silva, F., Cortez, M. C., and Armada, M. R. (2005) The persistence of European bond fund performance: does conditioning information matter? *International Journal of Business* **10**, 341-361.

ter Horst, J. R., Nijman, T. E., and Verbeek, M. (2001) Eliminating look-ahead bias in evaluating persistence in mutual fund performance. *Journal of Empirical Finance* **8**, 345-373.

Treynor, J. L. and Mazuy, F. (1966) Can mutual funds outguess the market? *Harvard Business Review* **44**, 131-136.

Zhao, X. (2005) Exit decisions in the U.S. mutual fund industry. *Journal of Business* **78**, 1365-1401.

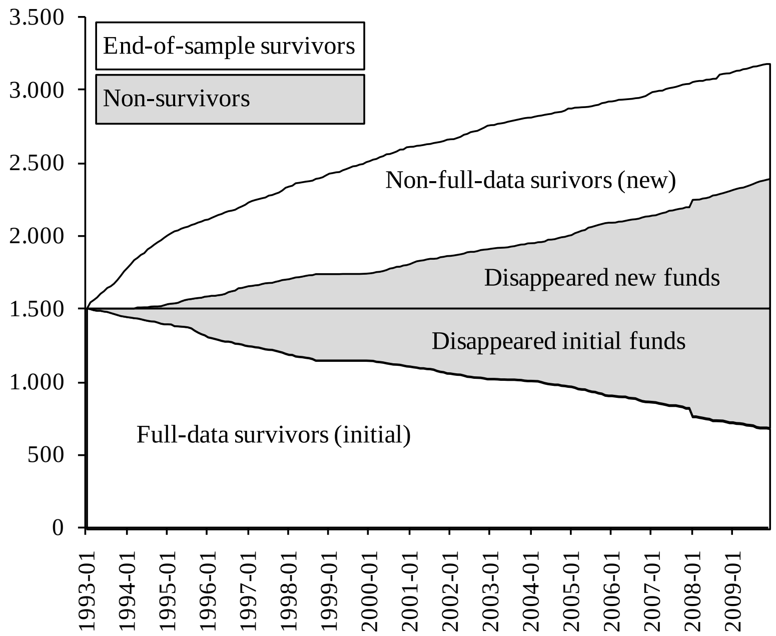

Figure 1. Sample development for the full sample 1993-2009

This figure shows how our full sample of 3,192 US bond mutual funds develops during our sample period from 01/1993 through 12/2009. Also the figure shows how the sample divides into different sub-groups with respect to the categories survival/disappearance and new/initial. In 01/1993 the sample starts with 1,512 initial funds and ends with 1,477 end-of-sample survivors in 12/2009 of which 686 have full data and 791 are non-full-data survivors. During the sample period 1,680 new funds enter the sample and 1,715 funds disappear of which 825 were already existed in 01/1993 (initial) and 890 started after 01/1993 (new).

Table I. Correlations between explanatory variables from the probit models

This table shows correlation coefficients between explanatory variables used for assessing the determinants of bond fund disappearance with different probit models. For a detailed description how these variables are constructed see the description of Table Z and the methodology chapter. The dotted boxes indicate that these variables are used alternatively. All correlations are denoted in percentage points.

	Relative Size (*t*-1*m*)	Log size (*t*-1*m*)	Expense ratio (*t*-1*m*)	Age (*t*-1*m*)	Relative return (*t*-1*y*)	Relative return (*t*-2*y*)	Relative return (*t*-3*y*)	Relative return (*t*1-5*y*)	Relative flow (*t*-1*y*)	Relative flow (*t*-2*y*)	Relative flow (*t*-3*y*)	Large : Return (*t*-1*y*)	Small : Return (*t*-1*y*)	Large : Flow (*t*-1*y*)	Small : Flow (*t*-1*y*)	Large (*t*-1*m*)
Log size (*t*-1*m*)	49.24															
Expense ratio (*t*-1*m*)	-18.47	-34.53														
Age (*t*-1*m*)	11.43	30.23	5.57													
Relative return (*t*-1*y*)	-1.49	0.43	5.19	0.09												
Relative return (*t*-2*y*)	2.67	1.79	-1.22	-2.86	-12.20											
Relative return (*t*-3*y*)	-0.38	-0.47	5.01	-1.34	2.04	13.57										
Relative return (*t*1-5*y*)	-1.16	-0.65	10.42	-2.67	41.09	49.31	51.13									
Relative flow (*t*-1*y*)	6.45	13.04	-6.64	-6.97	7.04	5.74	1.51	6.06								
Relative flow (*t*-2*y*)	7.56	12.77	-7.85	-8.69	-0.11	7.85	5.63	5.90	15.50							
Relative flow (*t*-3*y*)	4.42	7.84	-4.68	-8.72	-1.11	0.18	5.42	3.85	3.53	13.27						
Large : Return (*t*-1*y*)	-2.71	-2.00	5.08	2.13	59.05	-8.74	2.73	24.57	4.45	-0.30	-2.14					
Small : Return (*t*-1*y*)	0.17	2.27	0.63	-1.39	57.81	-5.67	-0.37	22.30	4.29	0.09	-0.59	0.00				
Large : Flow (*t*-1*y*)	2.77	-1.56	-2.16	-7.13	4.28	3.06	0.39	2.66	65.23	9.56	2.16	7.26	0.00			
Small : Flow (*t*-1*y*)	6.42	27.65	-7.36	1.96	5.40	2.93	1.45	4.41	41.42	8.66	2.97	-0.45	9.81	-1.19		
Large (*t*-1*m*)	34.01	71.28	-25.01	18.69	-1.61	-0.11	-1.83	-3.71	7.86	8.56	4.46	-2.78	-0.02	-7.40	16.02	
Small (*t*-1*m*)	-18.38	-69.74	21.04	-17.82	0.84	0.77	2.41	3.01	-8.01	-8.54	-5.78	1.33	0.03	3.53	-33.54	-47.77

Table II. Correlations between explanatory variables from the performance models

This table shows correlation coefficients between explanatory variables used for performance measurement with different multi index models (MIM) and asset class factor models (ACF). For a detailed list which US bond index (indices) represents which variable see Table A.3 in the Appendix and the data description chapter. The dotted boxes indicate which correlations are relevant for the respective models. All correlations are denoted in percentage points.

	Broad	Corporate	Government	Mortgage backed	Municipal	High yield	Risk free return	Corporate (mid)	Corporate (long)	Government (mid)
Corporate	79.84									
Government	80.41	33.18				*MIM-Risk*				
Mortgage backed	85.65	48.91	82.69			*ACF-Risk*				
Municipal	33.35	50.52	-3.53	21.23						*MIM-Maturity*
High yield	31.32	67.46	-26.95	1.05	50.72					
Risk free return	-17.10	-23.09	0.36	-22.96	-23.22	-21.31				
Corporate (mid)	74.78	98.28	26.68	45.76	54.26	68.62	-24.98			
Corporate (long)	82.33	95.98	41.13	50.62	41.22	60.97	-18.85	89.15		
Government (mid)	86.76	46.00	94.96	88.80	11.19	-9.85	-8.33	41.98	49.39	
Government (long)	86.90	48.88	92.57	82.08	7.47	-5.05	-1.33	38.52	61.52	89.71

Table III. Yearly fund starts and fund disappearances

This table shows fund starts (Panel I) and fund disappearances (Panel II) for the US bond fund market as a whole ("all classes") as well as for different asset classes in the period from 01/1993 through 12/2009. Fund start (disappearance) is defined as the first (last) return observation of a fund. The "absolute" figure reports the total number of fund starts (disappearances) observed in a particular year for a particular asset class. The "rate" figure reports the number of fund starts (disappearances) relative to the total number of funds existing at the beginning of the respective year, which is given in the data as the end of December value of the prior year. Average values are calculated as the simple mean of the yearly values. The "sum" reports the total number of fund starts (disappearances) in the sample period. The figure in parentheses reports the number of fund starts (disappearances) in a particular asset class relative to the number of fund starts (disappearances) in "all classes".

	All styles		Corporate		Government		Mortgage backed		Municipal		Money market		General bond	
	Absolute	Rate (%)	Absolute	Rate (%)	Absolute	Rate (%)	Absolute	Rate (%)	Absolute	Rate (%)	Absolute	Rate (%)	Absolute	Rate (%)
Panel I. Fund starts														
1993	255	17.24	59	17.25	55	29.73	15	22.06	52	21.76	71	11.29	3	25.00
1994	234	13.68	88	21.89	37	15.88	10	12.20	49	16.78	45	6.55	5	33.33
1995	119	6.37	45	9.49	15	5.91	5	5.62	12	3.66	41	5.84	1	5.00
1996	106	5.72	58	11.81	12	5.11	1	1.32	12	3.81	17	2.37	6	31.58
1997	117	6.43	56	10.69	11	5.12	4	5.97	8	2.68	34	4.92	4	16.00
1998	85	4.64	35	6.31	2	1.00	2	3.13	10	3.46	32	4.62	4	13.79
1999	91	4.97	40	7.14	6	3.17	2	3.28	9	3.16	27	3.84	7	21.88
2000	101	5.26	39	6.52	11	5.64	2	3.17	15	5.12	32	4.38	2	5.13
2001	53	2.76	27	4.55	1	0.54	0	0.00	4	1.39	21	2.75	0	0.00
2002	96	5.15	46	8.01	6	3.68	3	5.66	8	3.01	31	3.98	2	6.90
2003	55	2.93	29	5.01	3	1.94	3	5.36	9	3.44	10	1.26	1	3.70
2004	62	3.30	31	5.32	2	1.33	0	0.00	6	2.27	21	2.63	2	8.00
2005	48	2.60	18	3.13	5	3.42	1	1.92	4	1.54	15	1.89	5	20.83
2006	52	2.98	26	4.77	1	0.73	1	1.92	5	2.02	17	2.32	2	7.14
2007	70	4.10	27	4.99	7	5.51	2	3.85	14	5.93	15	2.07	5	17.24
2008	72	4.30	34	6.40	9	6.98	1	1.96	9	3.85	8	1.15	11	34.38
2009	64	4.17	16	3.02	8	6.40	3	6.00	12	5.24	7	1.25	18	43.90
Average 1993-2009	98.8	5.68	39.6	8.02	11.2	6.00	3.2	4.91	14.0	5.24	26.1	3.71	4.6	17.28
Average 1993-2006	105.3	6.00	42.6	8.71	11.9	5.94	3.5	5.11	14.5	5.29	29.6	4.19	3.1	14.16
Average 2007-2009	68.7	4.19	25.7	4.81	8.0	6.30	2.0	3.94	11.7	5.01	10.0	1.49	11.3	31.84
Average 1993-2001	129.0	7.45	49.7	10.63	16.7	8.01	4.6	6.30	19.0	6.87	35.6	5.17	3.6	16.86
Average 2002-2009	64.9	3.69	28.4	5.08	5.1	3.75	1.8	3.33	8.4	3.41	15.5	2.07	5.8	17.76
Sum (% of all classes)	1680	(100.00)	674	(40.12)	191	(11.37)	55	(3.27)	238	(14.17)	444	(26.43)	78	(4.64)

Table III. Continued.

	All styles		Corporate		Government		Mortgage backed		Municipal		Money market		General bond	
	Absolute	Rate (%)	Absolute	Rate (%)	Absolute	Rate (%)	Absolute	Rate (%)	Absolute	Rate (%)	Absolute	Rate (%)	Absolute	Rate (%)
Panel II. Fund disappearances														
1993	60	4.06	15	4.39	12	6.49	3	4.41	6	2.51	24	3.82	0	0.00
1994	79	4.62	15	3.73	19	8.15	3	3.66	13	4.45	29	4.22	0	0.00
1995	143	7.66	30	6.33	35	13.78	18	20.22	27	8.23	31	4.42	2	10.00
1996	131	7.07	25	5.09	31	13.19	10	13.16	25	7.94	40	5.58	0	0.00
1997	107	5.88	29	5.53	21	9.77	7	10.45	19	6.35	31	4.49	0	0.00
1998	75	4.10	24	4.32	14	6.97	5	7.81	13	4.50	18	2.60	1	3.45
1999	6	0.33	4	0.71	1	0.53	0	0.00	1	0.35	0	0.00	0	0.00
2000	104	5.42	46	7.69	20	10.26	9	14.29	23	7.85	0	0.00	6	15.38
2001	104	5.41	42	7.07	24	12.90	3	5.26	23	8.01	6	0.79	6	17.14
2002	87	4.67	41	7.14	13	7.98	0	0.00	12	4.51	17	2.18	4	13.79
2003	51	2.72	24	4.15	8	5.16	3	5.36	7	2.67	6	0.75	3	11.11
2004	96	5.12	42	7.20	8	5.33	4	7.14	10	3.79	29	3.63	3	12.00
2005	147	7.95	46	8.00	12	8.22	1	1.92	17	6.54	70	8.84	1	4.17
2006	93	5.34	33	6.06	11	8.03	1	1.92	17	6.88	30	4.09	1	3.57
2007	208	12.17	36	6.65	5	3.94	3	5.77	15	6.36	147	20.30	2	6.90
2008	109	6.52	34	6.40	13	10.08	2	3.92	14	5.98	43	6.18	3	9.38
2009	115	7.49	32	6.05	4	3.20	3	6.00	14	6.11	59	10.52	3	7.32
Average 1993-2009	100.9	5.68	30.5	5.68	14.8	7.88	4.4	6.55	15.1	5.47	34.1	4.85	2.1	6.72
Average 1993-2006	91.6	5.02	29.7	5.53	16.4	8.34	4.8	6.83	15.2	5.33	23.6	3.24	1.9	6.47
Average 2007-2009	144.0	8.73	34.0	6.37	7.3	5.74	2.7	5.23	14.3	6.15	83.0	12.33	2.7	7.86
Average 1993-2001	89.9	4.95	25.6	4.99	19.7	9.11	6.4	8.81	16.7	5.58	19.9	2.88	1.7	5.11
Average 2002-2009	113.3	6.50	36.0	6.46	9.3	6.49	2.1	4.00	13.3	5.36	50.1	7.06	2.5	8.53
Sum (% of all classes)	1715	(100.00)	518	(30.20)	251	(14.64)	75	(4.37)	256	(14.93)	580	(33.82)	35	(2.04)

Table IV. Summary statistics

This table shows summary statistics for the US bond fund market in the period from 01/1993 through 12/2009. The different columns show figures for the full-sample as well as for survivor/non-survivor and new/initial sub-groups. The different panels report figures for various sub-periods as well as for different asset classes. The average fund life in sample (months) and is calculated as the ratio between the number of monthly observations and the number of funds. Mean monthly net excess returns (%) are calculated as the cross-sectional mean of the time series mean net excess returns of all individual funds allocated to the respective fund group. Standard deviations (SD) are calculated as the cross-sectional standard deviation of all individual fund mean net excess returns. Mean size (Mio US$), mean age (months), mean yearly expense ratio (%), mean monthly percentage fund flow (%), and mean monthly absolute fund flow (Mio US$) are calculated analogously. *As we use aggregated data we do not remove funds with missing return data. Thus full-data survivors not necessarily show an average of 204 observations during the sample period. The same applies to the sub-periods with 168, 36, 108, and 36 observations, respectively. **As our data ends in 12/2009 we cannot identify which funds have their last appearance that month. Non-survivors thus have zero TNA in 12/2009. Before 12/2009 (e.g. 12/2006 or 12/2001) we can identify which funds have their last appearance that month, thus non-survivors not necessarily have zero TNA.

	Unbiased sample		Non-survivors		End-of-sample survivors		Full-data survivors		Non-full-data survivors		Initial funds		New funds		Initial disappeared funds		New disappeared funds	
[Average R_f = 0.29% (0.15%)]	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Panel I. All Styles 1993-2009																		
Number of funds	3,192		1,715		1,477		686		791		1,512		1,680		825		890	
% of all styles full-sample	100.00		53.73		46.27		21.49		24.78		47.37		52.63		25.85		27.88	
Number of monthly observations	352,386		133,207		219,179		138,457		80,722		217,339		135,047		78,851		54,356	
Average fund life in sample (months)	110		78		148		200*		102		144		80		96		61	
Monthly net excess return (%)	0.0654	(1.17)	0.0274	(1.10)	0.0886	(1.21)	0.0732	(1.12)	0.1151	(1.36)	0.0564	(1.09)	0.0801	(1.30)	0.0268	(1.02)	0.0283	(1.19)
Size (Mio US$)	1,276	(4,607)	395	(1,284)	1,841	(5,739)	2,278	(6,330)	1,096	(4,461)	1,610	(5,156)	751	(3,512)	481	(1,319)	275	(1,224)
Sum in 12/2009 (Mio US$)	4,401,209		-		4,401,209		2,863,054		1,538,154		2,863,054		1538154		-		-	
% of full-sample in 12/2009	100.00		-		100.00		65.05		34.95		65.05		34.95		-		-	
Age since inception (months)	129	(93)	102	(80)	146	(96)	189	(91)	73	(51)	171	(91)	63	(48)	139	(81)	49	(39)
Yearly expense ratio (%)	0.7291	(0.41)	0.7816	(0.44)	0.6956	(0.38)	0.7056	(0.35)	0.6782	(0.43)	0.7414	(0.37)	0.7092	(0.46)	0.8022	(0.40)	0.7522	(0.49)
Monthly percentage flow (%)	1.11	(12.4)	0.75	(13.8)	1.35	(11.4)	0.51	(8.7)	2.80	(14.9)	0.34	(9.6)	2.36	(15.8)	0.05	(11.1)	1.75	(17.0)
Monthly absolute flow (Mio US$)	6.89	(323)	-0.05	(115)	11.29	(402)	9.19	(376)	14.92	(445)	5.40	(305)	9.29	(350)	-1.04	(108)	1.35	(126)

Table V. Probit models of fund disappearance

This table shows results of a probit analysis of fund disappearance between 01/1993 and 12/2009 based on a pooled set of non-overlapping yearly observations. For non-survivors the month of reference for fund observations is the individual date of disappearance (e.g., 05/2000). In all years prior to disappearance these funds count as not disappeared, but the individual month of reference is kept (e.g., 05/1999, 05/1998, etc.). For survivors the month of reference in each year is December. Relative returns represent the total fund return less the average return of all funds. Relative flow is the percentage increase in total net assets of a fund less the average percentage increase in total net assets of all funds. Relative size is the size of a fund less the average size of all funds. Age represents the number of months since fund inception. (*t*-1*y*) indicates the 1-year-period prior to the month of reference, (*t*-2*y*) the 1-year-period prior to (*t*-1*y*), and (*t*-1*m*) indicates the month before the month of reference, etc. In Panel I, the models use combinations of different fund characteristics; the specifications follow Brown and Goetzmann (1995) and Rohleder et al. (2010) as well as four new model specifications. In Panel II, the models exclusively use one explanatory fund characteristic to explain fund disappearance. Large (Small) indicates that a fund ranks in the upper (lower) third with respect to size in (*t*-1*m*). p-values are computed using two-sided t-tests for regression coefficients and are based upon HAC-consistent covariances (Newey and West, 1987). The three R^2-statistics measure the model fit using the difference in maximum (log-)likelihood between a specific model and a respective null model.

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7		Model 8	
	Coefficient	p-Value	Coefficient	p-Value	Coefficient	p-Value	Coefficient	p-Value	Coefficient	p-Value	Coefficient	p-Value	Coefficient	p-Value	Coefficient	p-Value
Panel I. Models using multiple fund characteristics, All Styles 1993-2009																
Intercept	-1.7762	(0.00)	-1.8204	(0.00)	-0.6812	(0.00)	-0.6819	(0.00)	-0.7568	(0.00)	-0.6813	(0.00)	-0.5296	(0.00)	-0.6789	(0.00)
Log size (*t*-1*m*)					-0.2227	(0.00)	-0.2219	(0.00)	-0.2100	(0.00)	-0.2204	(0.00)	-0.2322	(0.00)	-0.2224	(0.00)
Expense ratio (*t*-1*m*)	30.7842	(0.00)	28.6080	(0.00)	7.2988	(1.84)	7.0561	(2.30)	7.5712	(2.83)	4.6829	(20.76)	2.2734	(54.47)	4.3296	(25.37)
Age (*t*-1*m*)	-0.0017	(0.00)	-0.0015	(0.00)	0.0003	(4.23)	0.0003	(4.87)	-0.0003	(10.31)	-0.0005	(3.35)	0.0000	(99.50)	-0.0004	(4.58)
Relative size (*t*-1*m*)	-0.0002	(0.00)	-0.0002	(0.00)												
Relative return (*t*-1*y*)	-0.9731	(0.00)			-0.8332	(0.07)	0.0900	(84.96)	0.4822	(27.44)			0.0497	(91.83)	0.6415	(15.96)
Relative return (*t*-2*y*)									-1.5975	(0.26)			-1.8799	(0.13)	-1.1039	(0.06)
Relative return (*t*-3*y*)													-1.5003	(3.72)	-1.3603	(0.08)
Relative return (*t*1-5*y*)			-4.3316	(0.00)												
Relative Flow (*t*-1*y*)									-0.5721	(0.00)	-0.7918	(0.00)			-0.7980	(0.00)
Relative Flow (*t*-2*y*)									0.0060	(63.15)	0.0120	(30.54)			0.0052	(78.84)
Relative Flow (*t*-3*y*)											-0.0449	(2.57)			-0.0486	(1.18)
Relative return (*t*-1*y*) : Large							-0.1048	(88.96)	1.9405	(4.73)			-0.1612	(83.49)	-0.3430	(62.21)
Relative return (*t*-1*y*) : Small							-1.4983	(0.88)	0.4381	(50.50)			-1.3031	(2.76)	-1.5137	(0.75)
Relative return (*t*-2*y*) : Large													1.1084	(28.80)		
Relative return (*t*-2*y*) : Small													0.3870	(58.76)		
Relative return (*t*-3*y*) : Large													0.2923	(82.30)		
Relative return (*t*-3*y*) : Small													-0.1316	(88.25)		
Relative flow (*t*-1*y*) : Large											-0.0406	(84.54)			-0.0175	(93.51)
Relative flow (*t*-1*y*) : Small											0.2591	(1.75)			0.2834	(1.19)
Nagelkerke R^2	6.33		7.01		14.17		14.24		16.94		16.40		14.10		16.82	
Pseudo R^2	2.10		2.13		4.64		4.66		5.42		5.16		4.42		5.26	
N	27,838		18,199		27,838		27,838		25,773		23,327		23,085		22,953	

Table V. Continued.

	Relative return 1		Relative return 2		Log size		Relative size		Expense ratio		Age		Relative flow 1		Relative flow 2	
	Coefficient	p-Value	Coefficient	p-Value	Coefficient	p-Value	Coefficient	p-Value	Coefficient	p-Value	Coefficient	p-Value	Coefficient	p-Value	Coefficient	p-Value
Panel II. Models using single fund characteristics, All Styles 1993-2009																
Intercept	-1.6728	(0.00)	-1.7039	(0.00)	-0.7740	(0.00)	-1.7667	(0.00)	-1.9134	(0.00)	-1.4735	(0.00)	-1.8638	(0.00)	-1.7578	(0.00)
Log size (*t*-1*m*)					-0.1886	(0.00)										
Expense ratio (*t*-1*m*)																
Age (*t*-1*m*)									34.5612	(0.00)						
Relative size (*t*-1*m*)							-0.0002	(0.00)			-0.0014	(0.00)				
Relative return (*t*-1*y*)	-0.1049	(79.30)														
Relative return (*t*-2*y*)	-1.5602	(0.00)														
Relative return (*t*-3*y*)	-1.4003	(0.06)														
Relative return (*t*1-5*y*)			-3.9062	(0.00)												
Relative Flow (*t*-1*y*)													-0.9211	(0.00)	-0.5608	(0.00)
Relative Flow (*t*-2*y*)													0.0068	(65.96)		
Relative Flow (*t*-3*y*)													-0.0262	(20.16)		
Relative return (*t*-1*y*) : Large	0.0764	(86.71)														
Relative return (*t*-1*y*) : Small	-2.0196	(0.11)														
Relative flow (*t*-1*y*) : Large															0.4401	(0.00)
Relative flow (*t*-1*y*) : Small															-0.4606	(0.00)
Nagelkerke R^2	0.95		0.56		11.56		3.54		1.65		1.02		5.77		6.51	
Pseudo R^2	0.31		0.17		3.73		1.16		0.54		0.33		1.85		2.16	
N	23,085		18,199		29,749		29,749		29,749		29,749		23,327		28,014	

Table VI. Fund Portfolio Performance

This table shows performance measures and factor loadings for equal-weighted (Panel I) and value-weighted (Panel II) fund portfolios of 9 differently composed fund groups in the period from 01/1993 through 12/2009. The “Full Sample” consists of all funds operating at any time during the sample period. Full-data and non-full-data survivors together add up to the end-of-sample survivors, which in combination with non-survivors add up to the full sample. New funds and initial funds also add up to the full sample. The table shows results for five different measures: the mean excess return (MER), a Single-Index-Model (SIM) using the excess return of a broad bond market index, two Multi-Index-Models using bond indices representing different asset classes (MIM-Risk) or maturities (MIM-Maturity), respectively, and a constrained Asset-Class-Factor model (ACF) based upon the MIM-Risk model. All results are based upon monthly aggregated excess return time series or, in case of the ACF model, on aggregated return time series. Value-weighted results are weighted by beginning of month TNA. All figures are quoted in percentage points per month. p-Values are reported in parentheses and computed using two sided t-tests for means and two-sided t-tests for regression coefficients, respectively. p-Values for regression coefficients are based upon HAC-consistent covariances (Newey and West, 1987). Pseudo R^2-statistics are calculated based upon log-likelihood measures following Verbeek (2004).

		SIM			MIM-Risk		ACF-Risk								MIM-Maturity								
	MER	Alpha	Broad	R^2 adj. / pseudo	Alpha	R^2 adj. / pseudo	Alpha	Gov	Corp	Muni	HY	Mort	Rf	R^2 adj. / pseudo	Alpha	Corp mid	Corp long	Gov mid	Gov long	Muni	HY	Mort	R^2 adj. / pseudo
Panel I. Equal-weighted 1993-2009																							
Unbiased sample	0.0693	-0.0406	47.15	74.77	-0.0526	96.87	-0.0526	9.38	10.30	14.57	7.60	8.17	49.98	-	-0.0579	18.82	-2.80	-2.18	6.50	13.95	7.19	9.87	96.83
	(10.08)	(17.00)	(0.00)	58.02	(0.00)	77.72	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	77.72	(0.00)	(0.00)	(25.54)	(56.38)	(6.66)	(0.00)	(0.00)	(0.00)	77.71
Non-Survivor	0.0165	-0.0935	45.49	71.67	-0.0924	90.51	-0.0935	14.20	8.14	16.37	7.07	0.00	54.23	-	-0.0970	20.24	-4.57	-5.52	10.37	16.06	6.13	3.81	89.60
	(69.02)	(0.05)	(0.00)	55.87	(0.00)	70.41	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(100.00)	(0.00)	70.41	(0.00)	(0.12)	(21.55)	(27.44)	(2.23)	(0.00)	(0.61)	(48.13)	69.68
End-of-Sample	0.0841	-0.0241	46.47	73.54	-0.0377	97.45	-0.0377	8.62	10.12	14.37	7.90	8.79	50.20	-	-0.0426	16.34	-1.72	0.20	5.21	13.87	7.58	9.52	97.25
	(4.52)	(42.28)	(0.00)	57.16	(0.00)	78.34	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	78.34	(0.00)	(0.00)	(48.68)	(95.66)	(13.85)	(0.00)	(0.00)	(0.00)	78.39
Full-Data	0.0741	-0.0254	42.73	68.27	-0.0402	96.84	-0.0402	6.71	6.97	17.82	7.99	8.13	52.38	-	-0.0451	15.98	-3.41	-2.88	5.05	17.08	7.66	9.85	96.97
	(6.43)	(39.46)	(0.00)	53.55	(0.00)	77.68	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	77.68	(0.00)	(0.00)	(21.14)	(49.83)	(13.13)	(0.00)	(0.00)	(0.00)	77.94
Non-Full-Data	0.1023	-0.0166	52.69	76.65	-0.0272	95.46	-0.0272	12.66	13.03	12.74	7.97	7.79	45.81	-	-0.0340	16.25	0.29	7.74	3.96	12.59	7.50	7.60	95.26
	(2.85)	(58.75)	(0.00)	59.34	(1.30)	75.67	(1.31)	(0.00)	(0.00)	(0.00)	(0.00)	(0.16)	(0.00)	75.67	(0.08)	(0.01)	(91.62)	(26.27)	(39.62)	(0.00)	(0.00)	(3.78)	75.51
Initial	0.0617	-0.0390	43.42	69.61	-0.0518	96.42	-0.0518	7.22	7.37	17.98	7.54	7.43	52.45	-	-0.0571	18.11	-4.19	-4.64	6.03	17.13	7.15	9.77	96.61
	(12.39)	(18.29)	(0.00)	54.47	(0.00)	77.04	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	77.04	(0.00)	(0.00)	(11.89)	(28.01)	(7.49)	(0.00)	(0.00)	(0.00)	77.38
New	0.0822	-0.0378	53.15	77.19	-0.0486	95.10	-0.0486	12.91	12.54	13.26	7.88	8.35	45.06	-	-0.0554	18.86	-1.27	3.68	5.60	12.94	7.31	9.63	94.75
	(7.96)	(21.47)	(0.00)	59.72	(0.01)	75.26	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.11)	(0.00)	75.26	(0.00)	(0.00)	(63.70)	(58.62)	(22.69)	(0.00)	(0.00)	(1.41)	74.89
Initial-Disappeared	0.0389	-0.0662	43.49	62.12	-0.0693	86.36	-0.0693	8.54	6.03	22.38	6.59	3.23	53.22	-	-0.0748	16.73	-3.51	-3.13	4.08	21.76	5.67	7.65	86.17
	(35.98)	(2.64)	(0.00)	49.39	(0.00)	66.86	(0.02)	(0.84)	(0.90)	(0.00)	(0.00)	(40.10)	(1.39)	66.86	(0.00)	(5.19)	(33.23)	(69.09)	(47.91)	(0.00)	(0.00)	(3.72)	66.81
New-Disappeared	0.0088	-0.1022	48.62	70.00	-0.1005	85.54	-0.1014	17.55	8.71	14.35	7.95	0.00	51.44	-	-0.1052	22.40	-5.38	-8.83	13.21	14.02	6.84	5.29	84.26
	(84.49)	(0.10)	(0.00)	54.73	(0.00)	66.21	(0.00)	(0.00)	(0.05)	(0.00)	(0.00)	(100.00)	(0.00)	66.20	(0.00)	(0.09)	(21.49)	(21.64)	1.75)	(0.00)	(1.83)	(49.85)	65.33

Table VI. Continued.

		SIM			MIM-Risk		ACF-Risk								MIM-Maturity								
	MER	Alpha	Broad	R^2 adj. / pseudo	Alpha	R^2 adj. / pseudo	Alpha	Gov	Corp	Muni	HY	Mort	Rf	R^2 adj. / pseudo	Alpha	Corp mid	Corp long	Gov mid	Gov long	Muni	HY	Mort	R^2 adj. / pseudo
Panel II. Value-weighted 1993-2009																							
Unbiased sample	0.0425	-0.0166	25.35	69.03	-0.0300	92.04	-0.0300	4.02	2.67	8.95	4.68	9.81	69.87	-	-0.0311	6.58	-1.03	-4.27	2.28	9.01	4.06	13.90	91.51
	(7.22)	(31.60)	(0.00)	54.07	(0.27)	71.87	(0.01)	(0.35)	(0.64)	(0.00)	(0.00)	(0.00)	(0.00)	71.87	(0.16)	(3.58)	(51.74)	(23.38)	(34.33)	(0.00)	(0.00)	(0.00)	71.35
Non-Survivor	0.0143	-0.0415	23.06	50.93	-0.0515	72.28	-0.0481	4.67	0.00	13.88	3.15	6.62	72.09	-	-0.0504	2.52	-2.99	-8.09	5.16	14.86	3.37	13.41	71.21
	(56.59)	(0.89)	(0.00)	41.75	(0.00)	56.67	(0.05)	(3.51)	(100.00)	(0.00)	(0.00)	(4.23)	(0.00)	56.21	(0.01)	(70.22)	(21.63)	(18.53)	(10.05)	(0.07)	(0.54)	(0.00)	56.15
End-of-Sample	0.0474	-0.0118	25.43	68.19	-0.0259	91.75	-0.0259	3.95	2.60	8.86	4.86	10.15	69.58	-	-0.0271	6.17	-0.89	-3.79	2.08	8.94	4.25	14.06	91.22
	(4.68)	(48.41)	(0.00)	53.49	(1.13)	71.59	(0.12)	(0.51)	(0.98)	(0.00)	(0.00)	(0.00)	(0.00)	71.59	(0.74)	(4.92)	(58.62)	(30.17)	(39.75)	(0.00)	(0.00)	(0.00)	71.16
Full-Data	0.0490	-0.0124	26.36	66.86	-0.0272	92.49	-0.0272	3.85	2.40	10.16	5.17	10.16	68.26	-	-0.0285	6.06	-0.95	-3.35	1.83	10.21	4.58	13.93	92.04
	(4.98)	(48.44)	(0.00)	52.59	(0.74)	72.33	(0.07)	(0.64)	(1.69)	(0.00)	(0.00)	(0.00)	(0.00)	72.33	(0.43)	(4.82)	(57.72)	(37.77)	(45.81)	(0.00)	(0.00)	(0.00)	71.96
Non-Full-Data	0.0468	0.0098	16.38	48.50	0.0083	64.69	0.0083	2.89	5.85	4.01	2.42	0.62	84.21	-	0.0050	2.33	2.38	9.65	-1.99	4.13	2.57	1.93	65.40
	(1.05)	(50.74)	(0.00)	40.07	(49.75)	51.60	(44.97)	(19.20)	(0.03)	(0.07)	(0.06)	(81.36)	(0.00)	51.60	(62.78)	(57.60)	(26.43)	(28.73)	(61.90)	(16.28)	(0.00)	(70.07)	52.30
Initial	0.0438	-0.0173	26.21	67.60	-0.0311	92.82	-0.0311	3.99	2.49	10.29	4.98	5.54	68.71	-	-0. 324	6.37	-1.03	-3.65	2.03	10.33	4.38	13.41	92.35
	(7.63)	(31.99)	(0.00)	53.09	(0.16)	72.67	(0.01)	(0.35)	(1.04)	(0.00)	(0.00)	(0.00)	(0.00)	72.67	(0.09)	(3.60)	(53.64)	(32.84)	(40.45)	(0.00)	(0.00)	(0.00)	72.26
New	0.0452	0.0020	19.15	56.99	-0.0026	71.89	-0.0026	3.56	5.07	4.76	2.84	3.72	80.05	-	-0.0057	3.95	1.34	5.72	-0.88	4.89	2.72	3.55	71.42
	(2.16)	(88.52)	(0.00)	45.91	(81.46)	56.41	(80.48)	(9.62)	(0.10)	(0.00)	(0.00)	(14.40)	(0.00)	56.41	(54.29)	(31.46)	(48.27)	(49.97)	(80.97)	(8.81)	(0.00)	(45.39)	56.29
Initial-Disappeared	0.0212	-0.0384	24.69	33.74	-0.0458	53.96	-0.0414	4.85	0.00	18.89	3.24	2.23	70.80	-	-0.0439	-1.53	1.43	4.42	3.60	20.39	3.66	9.35	52.77
	(51.50)	(10.66)	(0.00)	29.40	(2.31)	44.47	(8.46)	(19.25)	(100.00)	(0.00)	(0.07)	(68.36)	(0.00)	44.02	(3.05)	(86.39)	(66.90)	(65.69)	(51.65)	(0.59)	(3.38)	(2.39)	43.99
New-Disappeared	0.0214	-0.0257	20.64	64.52	-0.0395	77.50	-0.0393	3.70	0.00	5.57	3.59	13.47	73.68	-	-0.0411	7.24	-2.91	-7.61	2.70	5.44	2.83	19.62	77.57
	(28.03)	(4.21)	(0.00)	51.01	(0.01)	60.27	(0.02)	(1.89)	(100.00)	(0.00)	(0.00)	(0.00)	(0.00)	60.27	(0.00)	(20.51)	(16.18)	(19.05)	(29.10)	(0.25)	(0.73)	(0.00)	60.48

Table VII. Absolute and Relative Survivorship bias, and survivorship bias differences

This table shows absolue and relative survivorship bias estimates, and differences between survivorship bias estimates for different investment styles and in different time periods, displayed in different panels. Absolute Survivorship bias estimates are based upon the time series of return differences between survivor and full-sample portfolios (e.g. equal-weighted end-of-sample less equal-weighted full sample). Relative Survivorship bias represents the ratio of the absolute survivorship bias and the respective performance measure of the unbiased portfolio. (e.g. equal-weighted end-of-sample SIM survivorship bias less equal-weighted unbiased sample SIM). Survivorship bias differences are based upon the time series of return differences between the different survivorship bias time series described above. Value-weighted returns are weighted by beginning of month TNA. All figures are quoted in percentage points (per month). Reported p-values are computed using two-sided t-tests for means or for regression coefficients, respectively. p-Values for regression coefficients are based upon HAC-consistent coveriences (Newey and West, 1987). Allocation of funds to respective fund groups (e.g. full-data) is time period specific.

	Survivorship bias				Relative survivorship bias				Survivorship bias differences			
	End-of-sample		Full-data		End-of-sample		Full-data		End-of-sample vs. full-data		Equal- vs. value-weighted	
	Equal-weighted	Value-weighted	Equal-weighted	Value-weighted	Equal-weighted	Value-weighted	Equal-weighted	Value-weighted	Equal-weighted	Value-weighted	End-of-sample	Full-data
Panel I. All Styles 1993-2009												
MER	0.0149	0.0050	0.0048	0.0065	21.50	11.76	6.93	15.29	0.0100	-0.0016	0.0099	-0.0017
	(0.00)	(0.00)	(32.16)	(0.08)					(3.09)	(32.69)	(0.00)	(73.47)
SIM	0.0164	0.0048	0.0151	0.0042	40.39	28.92	37.19	25.30	0.0013	0.0006	0.0117	0.0109
	(0.00)	(0.00)	(0.00)	(1.80)					(71.20)	(64.75)	(0.00)	(0.03)
MIM-Risk	0.0149	0.0040	0.0124	0.0028	28.33	13.33	23.57	9.33	0.0025	0.0012	0.0108	0.0096
	(0.00)	(0.00)	(0.00)	(5.63)					(30.01)	(21.56)	(0.00)	(0.00)
ACF-Risk	0.0149	0.0041	0.0124	0.0028	28.33	13.67	23.57	9.33	0.0025	0.0012	0.0108	0.0096
	(0.00)	(0.00)	(0.00)	(1.67)					(24.65)	(11.47)	(0.00)	(0.00)
MIM-Maturity	0.0152	0.0040	0.0127	0.0026	26.25	12.86	21.93	8.36	0.0025	0.0015	0.0112	0.0101
	(0.00)	(0.00)	(0.00)	(5.07)					(25.17)	(9.90)	(0.00)	(0.00)

Table VIII. Performance of size-decile portfolios

This table shows statistics on size-decile portfolios in the period from 01/1993 through 12/2009. These portfolios are created by rebalancing individual funds monthly on the basis of their beginning of month TNA-ranks. The tenth decile represents the largest 10% of funds; the first decile represents the smallest 10% of funds. Mean TNA (MTNA) are denoted in million US$ and represent the mean of the aggregated TNA time series of a respective size-decile portfolio. All performance measures are denoted in percentage points and are based upon monthly excess return time series. Value-weighted returns are weighted by beginning of month TNA. p-Values are reported in parentheses and computed using two-sided t-tests for means and two-sided t-tests for regression coefficients, respectively. p-Values for regression coefficients are based on HAC-consistent covariances (Newey and West, 1987). The last three columns show the disappearance rates of funds allocated to a certain size-decile at any point in time within a one-month (t+1m), a one-year (t+1y), or a two-year period afterwards (t+2y), respectively. Disappearance rates are denoted in percentage points.

Size-decile	MTNA (Mio US$)	Equal-weighted performance				Value-weighted performance				Disappearance Rates		
		MER	SIM	MIM-Risk	MIM-Maturity	MER	SIM	MIM-Risk	MIM-Maturity	(t+1m)	(t+1y)	(t+2y)
Panel I. All Styles 1993-2009												
10 (Large)	9,067	0.0408	-0.0119	-0.0284	-0.0281	0.0368	-0.0076	-0.0206	-0.0213	0.0	0.7	1.5
		(7.74)	(50.86)	(4.08)	(3.67)	(4.78)	(57.87)	(10.78)	(8.19)			
9	1,922	0.0531	-0.0276	-0.0429	-0.0432	0.0431	-0.0349	-0.0511	-0.0506	0.1	1.3	2.8
		(12.44)	(33.82)	(0.00)	(0.00)	(19.99)	(22.67)	(0.00)	(0.00)			
8	893	0.0556	-0.0321	-0.0494	-0.0520	0.0454	-0.0405	-0.0581	-0.0599	0.1	1.7	3.5
		(12.72)	(30.31)	(0.00)	(0.00)	(19.97)	(17.07)	(0.00)	(0.00)			
7	523	0.0640	-0.0320	-0.0438	-0.0501	0.0516	-0.0423	-0.0540	-0.0590	0.2	2.5	5.1
		(11.04)	(33.69)	(0.13)	(0.01)	(18.13)	(17.76)	(0.00)	(0.00)			
6	328	0.0726	-0.0339	-0.0440	-0.0505	0.0614	-0.0417	-0.0517	-0.0576	0.2	3.2	7.0
		(9.68)	(36.40)	(0.55)	(0.05)	(14.37)	(23.48)	(0.04)	(0.00)			
5	200	0.0766	-0.0409	-0.0517	-0.0588	0.0686	-0.0465	-0.0580	-0.0647	0.4	4.6	9.3
		(8.98)	(20.87)	(0.01)	(0.00)	(12.0)	(14.20)	(0.00)	(0.00)			
4	120	0.0880	-0.0389	-0.0499	-0.0566	0.0727	-0.0503	-0.0609	-0.0667	0.4	5.6	11.0
		(5.99)	(13.97)	(0.00)	(0.00)	(10.69)	(4.30)	(0.00)	(0.00)			
3	68	0.0968	-0.0414	-0.0477	-0.0551	0.0823	-0.0511	-0.0570	-0.0640	0.5	6.4	12.2
		(5.46)	(14.63)	(0.00)	(0.00)	(9.02)	(5.77)	(0.00)	(0.00)			
2	32	0.0906	-0.0525	-0.0675	-0.0749	0.0813	-0.0570	-0.0710	-0.0781	0.8	9.7	18.5
		(9.43)	(14.86)	(0.00)	(0.00)	(11.78)	(8.97)	(0.00)	(0.00)			
1 (small)	8	0.0552	-0.0956	-0.1008	-0.1100	0.0711	-0.0818	-0.0855	-0.0940	1.6	15.3	26.1
		(32.01)	(0.38)	(0.00)	(0.00)	(21.59)	(2.58)	(0.00)	(0.00)			

Table IX. Survivor premium and size of non-survivors

This table shows performance differences between non-survivors (Panel I: all non-survivors, Panel II: liquidated, Panel III: merged) and end-of-sample survivors (survivor premium), as well as the size of non-survivors in the period from 01/1993 through 12/2005. Results are reported for the "full period" and for different time frames before fund disappearance (e.g., "Last" stands for the last year before disappearance, "2nd" for the second-to-last year, etc.). All performance measures are based upon the time series of differences between a respective disappeared fund portfolio and the end-of-sample survivor portfolio (e.g. equal-weighted non-survivor minus equal-weighted end-of-sample). Value-weighted returns are weighted by beginning of month TNA. Performance measures and significance levels are denoted in percentage points per month, size is denoted in million US$. Reported p-values are computed using two-sided t-tests for means and two sided t-tests for regression coefficients, respectively. p-Values for regression coefficients are based upon HAC-consistent covariances (Newey and West, 1987).

			Year before fund disappearance									
	Full period		Higher than 4th		4th		3rd		2nd		Last	
	Measure	p-Value	Measure	p-Value	Measure	p-Value	Measure	p-Value	Measure	p-Value	Measure	p-Value
Panel I. All Styles 1993-2005, 1,445 non-survivors												
Equal-weighted												
MER	-0.0254	(0.56)	-0.0079	(42.56)	-0.0044	(81.37)	-0.0374	(1.07)	-0.0478	(0.21)	-0.0461	(1.16)
SIM	-0.0456	(0.00)	-0.0247	(0.14)	-0.0327	(3.27)	-0.0575	(0.00)	-0.0699	(0.00)	-0.0712	(0.00)
MIM-Risk	-0.0428	(0.00)	-0.0207	(0.78)	-0.0274	(9.41)	-0.0581	(0.00)	-0.0734	(0.00)	-0.0707	(0.01)
MIM-Maturity	-0.0450	(0.00)	-0.0226	(0.22)	-0.0281	(8.59)	-0.0603	(0.00)	-0.0766	(0.00)	-0.0731	(0.01)
Value-weighted												
MER	-0.0307	(0.00)	-0.0212	(0.47)	0.0086	(73.77)	-0.0310	(25.81)	-0.0551	(0.98)	0.0085	(74.48)
SIM	-0.0387	(0.00)	-0.0286	(0.02)	-0.0279	(20.22)	-0.0573	(2.31)	-0.0674	(0.18)	-0.0152	(55.16)
MIM-Risk	-0.0358	(0.00)	-0.0257	(0.04)	-0.0215	(35.31)	-0.0663	(1.06)	-0.0701	(0.26)	-0.0109	(67.96)
MIM-Maturity	-0.0361	(0.00)	-0.0262	(0.01)	-0.0201	(39.22)	-0.0657	(1.47)	-0.0715	(0.14)	-0.0180	(49.14)
Size												
Mean TNA (Mio US$)	373		523		298		266		234		188	
Panel II. All Styles 1993-2005, 593 liquidated funds												
Equal-weighted												
MER	-0.0582	(0.00)	-0.0402	(0.33)	-0.0336	(12.90)	-0.0686	(0.00)	-0.0760	(0.00)	-0.1323	(0.02)
SIM	-0.0456	(0.00)	-0.0184	(8.43)	-0.0454	(6.84)	-0.0628	(0.01)	-0.0743	(0.00)	-0.1315	(0.03)
MIM-Risk	-0.0410	(0.00)	-0.0096	(15.30)	-0.0379	(10.06)	-0.0654	(0.00)	-0.0807	(0.00)	-0.1400	(0.10)
MIM-Maturity	-0.0425	(0.00)	-0.0109	(6.64)	-0.0371	(8.33)	-0.0667	(0.00)	-0.0844	(0.00)	-0.1437	(0.15)
Value-weighted												
MER	-0.0602	(0.37)	-0.0443	(4.32)	-0.0871	(0.54)	-0.0780	(0.19)	-0.0847	(0.01)	-0.0828	(0.05)
SIM	-0.0164	(19.90)	0.0002	(99.06)	-0.0971	(0.53)	-0.0594	(1.22)	-0.0651	(0.33)	-0.0641	(0.92)
MIM-Risk	-0.0076	(35.03)	0.0082	(39.84)	-0.0863	(1.39)	-0.0553	(1.70)	-0.0552	(0.50)	-0.0662	(1.48)
MIM-Maturity	-0.0062	(45.15)	0.0099	(31.18)	-0.0849	(1.58)	-0.0542	(2.60)	-0.0568	(0.30)	-0.0662	(1.18)
Size												
Mean TNA (Mio US$)	392		704		246		203		177		131	

Table IX. Continued.

	Full period		Year before fund disappearance									
			Higher than 4th		4th		3rd		2nd		Last	
	Measure	p-Value	Measure	p-Value	Measure	p-Value	Measure	p-Value	Measure	p-Value	Measure	p-Value
Panel III. All Styles 1993-2005, 852 merged funds												
Equal-weighted												
MER	-0.0067	(67.51)	0.0059	(74.29)	0.0034	(87.25)	-0.0209	(28.29)	-0.0342	(10.18)	0.0018	(93.15)
SIM	-0.0465	(0.00)	-0.0379	(0.00)	-0.0331	(4.05)	-0.0542	(0.05)	-0.0703	(0.00)	-0.0390	(0.92)
MIM-Risk	-0.0448	(0.00)	-0.0358	(0.00)	-0.0315	(7.38)	-0.0520	(0.19)	-0.0716	(0.00)	-0.0366	(1.78)
MIM-Maturity	-0.0473	(0.00)	-0.0374	(0.00)	-0.0313	(8.19)	-0.0545	(0.09)	-0.0746	(0.00)	-0.0379	(1.43)
Value-weighted												
MER	-0.0150	(36.43)	-0.0082	(72.50)	0.0202	(51.78)	-0.0351	(36.68)	-0.0396	(17.18)	0.0559	(12.04)
SIM	-0.0536	(0.00)	-0.0603	(0.00)	-0.0312	(21.20)	-0.0793	(2.21)	-0.0722	(0.49)	0.0096	(77.10)
MIM-Risk	-0.0536	(0.00)	-0.0592	(0.00)	-0.0295	(27.16)	-0.0943	(0.80)	-0.0756	(0.55)	0.0204	(53.78)
MIM-Maturity	-0.0547	(0.00)	-0.0590	(0.00)	-0.0284	(23.73)	-0.0932	(1.05)	-0.0764	(0.42)	0.0125	(70.13)
Size												
Mean TNA (Mio US$)	356		432		313		293		266		225	

Backup: Aus Version 18 gelöscht.

2. Literature review

In this paper we contribute to different strands in the mutual fund literature. First and foremost, we extend the research on fund disappearance and survivorship bias in fund performance to bond mutual funds as there has been little activity in this area before. Moreover, we contribute to the literature on bond fund performance by applying commonly used performance measures on different sub-groups to asses additional effects in bond fund performance.

There are very few articles systematically analyzing mutual fund disappearance in the previous literature. Brown and Goetzmann (1995) use probit models to analyze equity fund disappearance finding that fund returns play a major role as well as fund size and fund expenses. Rohleder et al. (2010) complement these findings by introducing dummy variables for large and small funds concluding that returns are especially important for survival and disappearance of small funds. Zhao (2005) uses multinominal logit models to analyze exit decisions in the mutual fund industry, concentrating on commonalities and differences of three different exit forms, namely liquidation and merger within or outside the fund family. Using data on equity, hybrid, and bond funds he finds that, in general, fund returns play a role but size is more important to all exit decisions. However, he states that there is no significant difference between the disappearance of bond funds and equity funds. We contribute to this strand of research by being, to our best knowledge, the first to examine the disappearance of bond funds in this detail.

The literature on survivorship bias mainly concentrates on equity mutual funds starting with Grinblatt and Titman (1989) and Brown et al. (1992). Today, it is common sense that an overstating survivorship bias in equity mutual fund performance exists and that it is also accountable for spurious performance persistence (e.g., Carhart, 1997). Among others, Brown and Goetzmann (1995), Malkiel (1995), Elton et al. (1996), Carhart et al. (2002), ter Horst et al. (2001), and Deaves (2004) contribute to this strand of literature using different definitions of survivorship bias. Rohleder et al. (2010) analyze the differences stemming from different definitions of survivorship bias finding that there are distinct differences between end-of-sample survivors and full-data survivors as well as between different weighting-schemes. In the case of bond mutual funds there is only very scarce evidence on survivorship bias. Blake et al. (1993), who are the first to thoroughly analyze bund fund performance, state that survivorship bias is unimportant to bond funds. Since then, many studies refer to this statement. A popular argument is that survivorship bias overstates results that are anyway negative (e.g., Elton et al., 1995; Detzler, 1999; Silva et al., 2005; Polwitoon and Tawatnntachai, 2006). We contribute to this literature by being the first to analyze survivorship bias in bond mutual fund performance and the economic relations behind it based upon a comprehensive dataset.

The third strand of literature our paper is related to is bond fund performance. Blake et al. (1993) analyze the performance of a wider range of bond funds by applying CAPM-related single-index models (SIM), Multi-index models (MIM), and constrained asset-class-factor models (ACF) finding that bond funds under-perform passive benchmarks after fees, while performing on par on a before-fees basis. In their following study, Elton et al. (1995) first apply ATP-models using unexpected changes in economic variables in addition to passive benchmarks finding that performance results remain qualitatively the same while the model fit improves significantly.

Cornell and Green (1991) analyze the performance of low-grade bond funds finding that these funds are less sensitive to interest rate movements than to changes in stock prices due to shorter durations. Redman and Gullet (2006) draw similar conclusions for municipal bond funds. John Kihn (1996) also analyzes low-grade municipal funds focusing on the effect of embedded options finding that at times low-grade municipal funds out-perform high-grade municipal bond funds on a risk-adjusted basis. Philpot et al. (1998) analyze conventional bond fund performance finding that bond funds under-perform passive benchmarks and document economies of scale such that larger funds out-perform smaller funds. Philpot et al. (2000) document similar results for nonconventional bond funds and short-term persistence in high-yield bond funds.

Ghallager and Jarnecic (2002) apply unconditional and conditional performance models to Australian bond funds finding that active management does not add value after fees and that fund flows erode timing performance. Silva et al. (2005) also apply conditional performance measures on European government bonds finding evidence for performance persistence, especially in Spanish bond funds. Dietze et al. (2009) assess the performance of European investment grade corporate bonds also finding consistent negative risk-adjusted performance. Detzler (1999) as well as Polwitoon and Tawatnuntachai (2006) analyze US based global bond funds and conclude that these under-perform benchmark indices but provide diversification benefits to US equity investors.

Ferson et al. (2006) are the first to measure conditional performance of US government bond funds via stochastic discount factors also finding that bond funds under-perform after fees. Huij and Derwall (2008) document significant “hot hands” in bond fund performance suggesting an investment strategy to exploit persistence. Chen et al. (2010) measure timing abilities of bond fund managers adjusting for natural non-linearity caused by benchmark assets, interim trading, conditioning information, and stale prices. They find none or weakly positive timing abilities. Very recently, Cici and Gibson (2010) analyze corporate bond fund performance based upon detailed holdings information finding that managers show negative selection performance but weakly positive timing ability.

We contribute to this strand of literature by applying the most commonly used performance models on a variety of bond fund groups, namely different asset classes, different sub-periods, different sizes, and different survivor/non-survivor and initial/new sub-groups. This allows many comparisons and conclusions on differences between the groups, over time and between funds with different characteristics.

Grund: größtenteils redundant mit der Einleitung.

———

FN auf S. 28 (Kapitel 4.3.)

The performance of deciles between the extremes is on a medium level and more or less equal for all deciles. We test this by analyzing the differences between the extreme deciles 1 and 10 and the other deciles. We find that the smallest 10 % of funds (decile 1) significantly under-perform all other deciles. The largest 10 % of funds (decile 10) significantly out-perform most other deciles when portfolios are value-weighted. For equal-weighting the differences are not significant except for the differences between decile 10 and the deciles 1 and 2. Due to space limitations, these results are not displayed in the paper but available from the authors upon request. While value-weighted portfolios show slightly higher performance, neither equal-weighted nor value-weighted size-decile portfolios show positive alphas.

Grund: Wenig Mehrwert durch zu große Detailliertheit.

———

Methoden-Kapitel, letzter Absatz vor den Performance Measures.

For our analysis of new funds we use a similar approach, except that we split the time series into five segments according to the time frame after fund start to construct our new fund portfolios. To directly show whether and when new funds perform differently from other funds we calculate return differences between new funds and initial funds. Here, we limit the time period to 01/1997 through 12/2009.

4.5 NEW FUNDS VS. INITIAL FUNDS

In our performance analysis we find that non-full-data survivors perform exceptionally well and new funds in general out-perform initial funds. This raises the question whether this is due to superior fund management or evidence for fund incubation (e.g., Evans, 2010) which could bias our results. Therefore, we analyze in this section the performance of new funds in further detail by assessing performance differences between new funds and initial funds ("new fund premium") in the full period and in different time frames after fund start.

Panel I of Table X shows the new fund premium for both equal- and value-weighted portfolios based upon the full-sample in the period from 01/1997 through 12/2009. Most importantly, only very few of the figures are significantly different from zero. Moreover, there is no clear systematic pattern to be discovered because negative and positive signs can be found in all time frames. There are, however, two exceptions. In the 3rd year after fund start, equal-weighted new funds significantly under-perform and value-weighted new funds also show their highest under-performance, but without statistical significance. And value-weighted new funds show consistent out-performance in their first year, but again without statistical significance for all risk-adjusted measures. In terms of size, it is no surprise that new funds start relatively small in their first year and grow constantly over time.

[Insert Table X here.]

Another interesting finding is that MER is distinctly higher than the alpha measures for all equal-weighted portfolios and time frames as well as for many value-weighed portfolios and time-frames. This suggests that new funds in general take relatively high risk. As a consequence, those who succeed survive and drive the high performance of non-full-data survivors while those who fail disappear to constitute the clear under-performance of new disappeared funds. Supporting evidence can be found in Table VI where new disappeared funds show the worst performance for all performance measures.

Over time, the picture of the new fund premium is much more differentiated. Panels II-V of Table X (upon request) show the new fund premium in various sub-periods (1997-2006 and 2007-2009; 1997-2001 and 2002-2009). The results show that in earlier periods new funds significantly out-perform initial funds in their 1st year by up to 1.03 % p.a. (1997-2001) or 0.58 % p.a. (1997-2006), respectively, while under-performing in later years. Also, new funds out-perform over the full-period by up to 0.41 % p.a. (1997-2001). This is a clear sign of incubation during earlier sub-periods. In the later periods the results are much less systematic with the worst under-performance in the 3rd year, the highest out-performance in the 4th year, and slight under-performance in the full-period. This closely corresponds to the findings of Evans (2010) who documents that the incubation practice was most popular during earlier years and decreased in later years.

For different asset classes Panels VI-XI of Table X (upon request) also show very different results. We find evidence for fund incubation within corporate and municipal bond funds. New funds from both asset classes show their best performance and mostly even out-performance in their 1st year while under-performing in later years. On the other hand, new government bond funds show very unsystematic results with the exception that their worst under-performance is in their 1st year which we interpret as evidence against incubation. Mortgage backed bond funds show related results in that they perform worst in their 1st and 2nd year while performing better afterwards. But in contrast to new government bond funds, new mortgage backed bond funds out-perform initial funds in the full period and over most time frames. New money market funds consistently out-perform initial money market funds during all time frames. In doing so they show their worst performance in the 1st and 2nd year and their best performance in their 4th year or later; so again evidence against incubation. General bond funds show very unsystematic results with no clear evidence in favor or against incubation, but with their best performance consistently in later time frames.

In a nutshell: We find evidence for fund incubation primarily in earlier periods which closely corresponds to the findings in the literature. Moreover, we find evidence for fund incubation for corporate and municipal bond funds while the other styles show no signs of incubation bias. In terms of size, new funds from all asset classes start small and grow very fast during their first years of existence. Moreover, we document that new funds take relatively high risk. This explains why non-full-data survivors out-perform while new disappeared funds under-perform all other sub-groups in the performance analysis.

Grund: Passt inhaltlich nicht 100%ig zum Rest. Falls vom Referee gefordert kann es aber wieder ins Paper rein. -> Überarbeiten!

Literaturverzeichniseintrag:

Evans, R. B. (2010) Mutual fund incubation. *Journal of Finance* **65**, 1581-1611.

Table X. New Funds: New fund premium and fund size

This table reports the performance differences between new funds and initial funds (Panel I), new funds and the full sample (Panel II) as well as the fund size of new funds (Panel I) in the period from 01/1997 through 12/2009. Within this period the table shows figures for the "full period" as well as measures for different time frames after fund start (e.g., "1st" standes for the first year of existence, etc.). All performance differences are based upon the time series of return differences between a new funds portfolio and the initial funds or full sample portfolio, respectively (e.g., equal-weighted new 1st less equal-weighted initial). Value-weighted returns are weighted by beginning of month TNA. Performance differences and p-values are denoted in percentage points. p-Values are reported in parentheses and are computed using two-sided t-tests for means and two-sided t-tests for regression coefficients, respectively, and are based upon HAC-consistent covariances (Newey and West, 1987).

			Year after fund start									
	Full period		1st		2nd		3rd		4th		5th and higher	
	Measure	p-Value	Measure	p-Value	Measure	p-Value	Measure	p-Value	Measure	p-Value	Measure	p-Value
Panel I. All Styles 1997-2009, new funds vs. initial												
Equal-weighted												
MER	0.0202	(9.70)	0.0361	(19.03)	0.0347	(15.41)	-0.0081	(77.93)	0.0183	(41.60)	0.0174	(7.65)
SIM	-0.0038	(66.97)	-0.0109	(64.44)	-0.0061	(73.43)	-0.0547	(3.32)	-0.0131	(51.73)	0.0010	(90.65)
MIM-Risk	-0.0011	(85.65)	-0.0059	(76.16)	0.0098	(54.67)	-0.0488	(7.94)	-0.0140	(45.49)	0.0038	(53.62)
MIM-Maturity	-0.0002	(97.69)	0.0042	(81.60)	0.0093	(55.79)	-0.0425	(8.09)	-0.0212	(25.98)	0.0047	(46.55)
Value-weighted												
MER	-0.0039	(64.28)	0.0660	(4.40)	-0.0039	(83.03)	-0.0213	(45.84)	0.0408	(11.79)	-0.0096	(30.36)
SIM	0.0068	(37.69)	0.0226	(45.44)	-0.0178	(45.44)	-0.0526	(12.57)	0.0339	(17.10)	0.0052	(50.09)
MIM-Risk	0.0090	(11.82)	0.0286	(28.64)	0.0084	(61.34)	-0.0379	(25.59)	0.0335	(30.28)	0.0063	(28.14)
MIM-Maturity	0.0096	(5.56)	0.0354	(14.43)	-0.0092	(58.57)	-0.0284	(26.73)	0.0208	(45.27)	0.0071	(17.96)
Size												
Mean TNA (Mio US$)	806		251		372		512		685		989	