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Status Quo Bias and the Number of Alternatives - An Empirical Illustration from the Mutual Fund Industry -

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Abstract

We examine the extent of the Status Quo Bias (SQB) in a real-world repeated decision situation. Individuals who are subject to a SQB tend to choose an alternative that was chosen previously (i.e. their status quo), even if it is not the optimal choice any more. We examine the US equity mutual fund market and find strong evidence for the existence of a SQB in this market. Furthermore, the SQB is more severe in segments where there are more funds to choose from. Thereby, we deliver the first empirical confirmation of the experimental result of Samuelson and Zeckhauser (1988), that the SQB positively depends on the number of alternatives.

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Keywords: Status Quo Bias, Mutual Funds, Number of Alternatives, Performance Flow Relationship

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Abstract

We examine the extent of the Status Quo Bias (SQB) in a real-world repeated decision situation. Individuals who are subject to a SQB tend to choose an alternative that was chosen previously (i.e. their status quo), even if it is not the optimal choice any more. We examine the US equity mutual fund market and find strong evidence for the existence of a SQB in this market. Furthermore, the SQB is more severe in segments where there are more funds to choose from. Thereby, we deliver the first empirical confirmation of the experimental result of Samuelson and Zeckhauser (1988), that the SQB positively depends on the number of alternatives.

1 Introduction

This paper is concerned with the status quo bias (SQB) in the mutual fund market. We examine how the extent of the SQB depends on the number of alternatives offered.

Individuals are subject to a SQB, if they tend to select an sub-optimal alternative, just because that alternative was chosen before.[1] For example, an investor is subject to a SQB if she buys a specific stock just because she did so in a previous investment decision, even if this stock is suboptimal given the investor's situation at hand. It is well documented in the literature, that individuals are subject to a SQB when it comes to making financial decisions: Samuelson and Zeckhauser (1988) examine the pension plan decisions of Harvard employees and find that they are subject to a SQB. Ameriks and Zeldes (2001) look at the portfolio holdings of private households and report that the composition of their portfolios is rarely and only slightly changed. A similar effect is reported by Agnew, Balduzzi, and Sunden (2003) who look at the pension accounts of US investors. Barber, Odean, and Zhu (2003) report that investors tend to buy those stocks they bought before. All of these results can be interpreted as supportive of the existence of a SQB.

The SQB in the context of the purchase decisions of mutual fund investors has been addressed by Patel, Zeckhauser, and Hendricks (1991) and (1994). They present empirical evidence that fund investors tend to buy those funds they already bought in the past. A similar phenomenon is reported by Agarwal, Daniel, and Naik (2004) for hedge fund investors. The results of these studies are also consistent with the idea that fund investors are subject to a SQB.

In an experimental study, Samuelson and Zeckhauser (1988) find that the extent to which individuals are subject to a SQB positively depends on the number of alternatives they have to choose from.[2] However, to our best knowledge, there is no empirical evidence from a real world situation that documents the dependence of the SQB on the number of alternatives.[3] Our study fills this gap by empirically examining how the extent of the SQB in the mutual fund market dependens on the number of alternatives offered.

Empirical studies of the fund industry have proven to be a useful natural experiment to test behavioral anomalies (see, e.g., Goetzmann, Massa, and Rouwenhorst (2000)) for two reasons: firstly, because mutual funds are a preferred investment vehicle for unsophisticated investors who do not want to directly participate in the stock market themselves. One can argue that behavioral anomalies like the SQB are more important in such retail markets, than in markets where mainly sophisticated specialists are trading amongst each other. Secondly, real world situations are preferable to experimental situations, because in real world situations the participating individuals have considerable real money at stake and will therefore be much more careful to act in a rational way (Samuelson and Zeckhauser (1988)). The disadvantage if we look at real world data instead of results from controlled laboratory experiments is that there are many other possible influences that might drive the observed results (see Section 5.4).

To examine the existence of a SQB in the mutual fund market, we analyze how inflows into a fund depend on previous inflows into the same fund. We examine the influence of previous external growth (i.e. growth due to net-inflows of new money) for various segments of the mutual fund industry separately.[4] The number of alternatives for mutual fund investors in each segment is given by the number of funds in that segment. As this number varies considerably between different segments, this allows us to examine the influence of the number of alternatives on the SQB in a real-world situation. Based on the experimental evidence in Samuelson and Zeckhauser (1988), we expect the influence of previous fund inflows on present fund inflows to be stronger in segments with a lot of alternatives than in segments with only a small number of funds.

Our empirical study of the U.S. equity mutual fund market provides strong evidence for a positive dependence of the extent of the SQB on the number of alternatives offered. This supports our hypothesis that the extent of the SQB in repeated decisions depends on the number of alternatives.

Our results contribute to a better understanding of the behavior of mutual fund investors. Furthermore, they also have relevant implications for fund families[5] and fund managers. If a family offers a fund in a large segment, a good performance will lead to much more persistent inflows than if it belongs to a small segment. There is some evidence that families might be able to selectively push the performance of a particular fund (Guedj and Papastaikoudi (2004) and Gaspar, Massa, and Matos (2004)). Our results suggest to, ceteris paribus, push the performance of those funds that belong to large segments. In these segments there is not only a direct effect on growth via the positive performance-flow relationship, but also an additional long-term indirect positive effect from the greater flow-persistence. Furthermore, our results can help fund managers (who get paid dependent on their assets under management (Khorana (1996)) to predict their earnings. An increase due to increased fund growth will be more persistent in larger segments.

In Section 2 we introduce our empirical model and in Section 3 we present our data and summary statistics. Section 4 presents our results. Robustness tests and possible limitations of our results are discussed in Section 5. Section 6 concludes.

2 Empirical Model

We examine the extent of the SQB in the mutual fund market by looking at the influence of previous net inflows on present net inflows. However, as there are many other variables that have proven to influence fund growth, a model relating current fund growth to previous fund growth exclusively would be too simplified. We know that investors base their investment decisions on previous performance (see, e.g. Sirri and Tufano (1998)), but also other fund related characteristics. Therefore, we will test the following model:

$$FLOW_{i,t} = f(FLOW_{i,t-1}, Perf_{i,t-1}, \textbf{Controls}), \tag{1}$$

where $FLOW_{i,t}$ denotes the growth of fund i in year t, which is due to the inflow of new money. $Perf_{i,t-1}$ denotes the performance of the fund in the previous year, $t-1$. **Controls** is a vector of control variables (see Section 2.2).

2.1 Dependent Variable

Based on previous work (e.g. Sirri and Tufano (1998), and Chevalier and Ellison (1997)), we define the external growth of a fund i in year t that is due to inflows of new money as:

$$FLOW_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}}{TNA_{i,t-1}} - r_{i,t},$$

where $TNA_{i,t}$ are the assets under management of fund i at the end of year t and $r_{i,t}$ is the rate of return of fund i in year t. We use this synthetic measure of external fund growth, because our database does not contain explicit net-flows. $FLOW_{i,t}$ is a conservative measure of fund growth. It implicitly assumes that all flows occur at the end of the year and that dividends are completely re-invested.[6]

2.2 Independent Variables

Our main independent variable of interest is the growth of the fund in the previous year, $FLOW_{i,t-1}$. If the external growth of a fund positively depends on its external growth in the previous year, this indicates that its investors are subject to a SQB. However, a positive dependence could also be due to other characteristics of the fund that do not change over time and that are important determinants of fund investors' purchase decisions. Therefore, we have to control for these (potential) influences on fund growth.

First of all, it is a well-established fact that the growth of a fund depends on its prior performance (see, e.g., Spitz (1970) and Smith (1978)). We use ordinal ranks based on raw returns as performance measure. To calculate these ranks we sort all funds from a segment according to their raw return and assign a rank number to them in descending order. This rank is then normalized, so that rank numbers are evenly distributed between 0 and 1. The best fund in a segment gets assigned the rank number 1. We use return ranks, because ranks can explain fund growth much better than cardinal measures and because returns are able to explain fund growth very well (see, e.g., Patel et al. (1991), and Harless and Peterson (1998)).[7]

We now turn to a description of the variables contained in **Controls**:

$Std_{i,t}$ denotes the annualized standard deviation of fund i's return in t. A negative influence of $Std_{i,t}$ indicates that fund investors are risk averse and prefer funds that showed a low return-volatility in the past. Sirri and Tufano (1998) find a negative but insignificant influence of a fund's risk on its external growth.

$Age_{i,t}$ denotes the age of fund i in year t. The age of a fund might impact its behavior (see, e.g., Chevalier and Ellison (1997)). The inclusion of $Age_{i,t}$ allows us to determine whether investors prefer new funds or older funds. Bergstresser and Poterba (2002) and DelGuercio and Tkac (2002) report that older funds grow slower than younger funds.

The size of fund i in year t is given by its assets under management, $TNA_{i,t}$. The literature reports a negative influence of size on fund growth, indicating that it is easier for smaller funds to grow (on a relative basis) than for older funds (see, e.g., Chevalier and Ellison (1997), and Sirri and Tufano (1998)).

Fees also play an important role in explaining fund growth (see, e.g., Sirri and Tufano (1998), Khorana and Servaes (2004), and Barber, Odean, and Zheng (2004)). We follow the literature and assume an average holding period of seven years (see Sirri and Tufano (1998)). Therefore, our measure for the fee burden of a fund, $Fees_{i,t}$, is calculated by adding the expense ratio of a fund to 1/7th of the front-end load.[8]

The turnover rate, $TO_{i,t}$ is also a factor potentially influencing fund growth. A positive coefficient would be indicative of investors preferring an active investment style. Whereas Bergstresser and Poterba (2002) find a positive influence of trading activity on fund growth, Woerheide (1982) finds no significant relationship.

Many families offer their investors the opportunity to switch between the family's funds at no cost. This represents a switching option for fund investors (see, e.g., Siggelkow (2003)). The value of this option positively depends on the number of other funds offered by the same family. Therefore, we add the number of funds offered by the family the fund belongs to, $Numb_{i,t}$, as additional explanatory variable. A positive influence of $Numb_{i,t}$ on fund growth is consistent with investors placing a positive value on the switching option.

Finally, we add the growth of the segment and of the family a fund belongs to, $FLOW_{i,t}^{Seg}$ and $FLOW_{i,t}^{Fam}$, respectively, as explanatory variables. This allows us to control for other segment- or family-specific determinants that influence fund growth. A positive influence of $FLOW_{i,t}^{Seg}$ and $FLOW_{i,t}^{Fam}$ is reported in Fant and O'Neal (2000) and Kempf and Ruenzi (2004), respectively.

Our complete empirical model reads:

$$\begin{aligned} FLOW_{i,t} = \; & b_1 \cdot FLOW_{i,t-1} + b_2 \cdot Perf_{i,t-1} + b_3 \cdot Std_{i,t-1} \\ & + b_4 \cdot lnTNA_{i,t-1} + b_5 \cdot lnAge_{i,t} + b_6 \cdot Fees_{i,t-1} \\ & + b_7 \cdot TO_{i,t-1} + b_8 \cdot FLOW_{i,t}^{Seg} + b_9 \cdot FLOW_{i,t}^{Fam} \\ & + b_{10} \cdot lnNumb_{i,t-1}^{Fam} + \sum_{j=1993}^{2001} a_j \cdot D_j, \end{aligned} \tag{2}$$

where D_j is a dummy variable which takes on the value one if an observation is from year t, and zero otherwise. They allow us to control for year-specific effects. We use these dummies, because we pool observations from all years in one regression. Note, that we include all variables whose values are not known to investors at the beginning of year t with their $t-1$ values. Furthermore, we include the logarithm of the size and age of the fund, because we do not expect a linear influence of these variables (see, e.g., Sirri and Tufano (1998)).

2.3 Convexity of the Performance Flow Relationship

Chevalier and Ellison (1997) and Sirri and Tufano (1998), among others, show that the relationship between $Perf_{i,t-1}$ and $FLOW_{i,t}$ is convex. To account for this convexity, we use two approaches that are suggested in the literature: (a) we add $Perf_{i,t-1}^2$ in our regression (see, e.g., Barber et al. (2004)):

$$\begin{aligned} FLOW_{i,t} = \; & b_1 \cdot FLOW_{i,t-1} + b_{2a} \cdot Perf_{i,t-1} + b_{2b} \cdot Perf_{i,t-1}^2 \\ & + b_3 \cdot Std_{i,t-1} + b_4 \cdot lnTNA_{i,t-1} + b_5 \cdot lnAge_{i,t} \end{aligned}$$

$$
\begin{aligned}
&+b_6 \cdot Fees_{i,t-1} + b_7 \cdot TO_{i,t-1} + b_8 \cdot FLOW_{i,t}^{Seg} \\
&+b_9 \cdot FLOW_{i,t}^{Fam} + b_{10} \cdot lnNumb_{i,t-1}^{Fam} \\
&+ \sum_{j=1993}^{2001} a_j \cdot D_j
\end{aligned} \tag{3}
$$

(b) we apply a piecewise linear regression approach (see, e.g., Sirri and Tufano (1998)). With this approach the slope coefficients for the lowest quintile, for the three middle quintiles, and for the top quintile of the fractional performance ranks are estimated separately

$$
\begin{aligned}
FLOW_{i,t} \quad = \quad & b_1 \cdot FLOW_{i,t-1} + b_{low} \cdot LOW_{i,t-1} + b_{mid} \cdot MID_{i,t-1} \\
& +b_{high} \cdot HIGH_{i,t-1} + b_3 \cdot Std_{i,t-1} + b_4 \cdot lnTNA_{i,t-1} \\
& +b_5 \cdot lnAge_{i,t} + b_6 \cdot Fees_{i,t-1} + b_7 \cdot TO_{i,t-1} \\
& +b_8 \cdot FLOW_{i,t}^{Seg} + b_9 \cdot FLOW_{i,t}^{Fam} \\
& +b_{10} \cdot lnNumb_{i,t-1}^{Fam} + \sum_{j=1993}^{2001} a_j \cdot D_j,
\end{aligned} \tag{4}
$$

where

$$
\begin{aligned}
LOW_{i,t-1} &= \min(Perf_{i,t-1}, 0.2) \\
MID_{i,t-1} &= \min(Perf_{i,t-1} - LOW_{i,t-1}, 0.6) \\
TOP_{i,t-1} &= Perf_{i,t-1} - (LOW_{i,t-1} + MID_{i,t-1}).
\end{aligned}
$$

For example, the slope coefficient for the relationship between $FLOW_{i,t}$ and $Perf_{i,t-1}$ in the lowest quintile of the fractional return ranks is then given by b_{low}.[9]

3 Data and Summary Statistics

We use data from the CRSP survivorship free mutual fund database.[10] The CRSP database contains data on monthly total returns, the fund management company, the year of origin, and other characteristics of the fund. To define the market segments mutual funds are doing business in we use the Strategic Insight Objectives (SI), which is a fund classification provided in the CRSP database. As the SI classification is available from 1993 on, our study starts in 1993. It ends in 2001 leaving us with nine years of data. We exclude all bond and money market funds. Furthermore, we only use observations for which all data are completely available.

To prevent our results from being biased by the extreme growth rates of some outliers, we winsorized the growth rates of all funds that grow by more than 500%. Overall, our sample contains 20.193 yearly fund observations from 38 different segments and 383 different fund families. An overview of our dataset is given in Table 1.

+ + + PLEASE INSERT TABLE 1 ABOUT HERE + + +

The number of funds in our dataset grows more than fourfold from 936 in 1993 to 4.319 in 2001. On average, a fund manages more than 700 million USD. The average growth rate ($FLOW$) of all funds is nearly 20% p.a. In 1993 the average growth rate is very high at nearly 40%. The average age of a fund is nine years, but it steadily declines from nearly 14 years in 1993 to only about 8 years in 2001. This trend is due to the emergence of a lot of new funds in the late 1990s. The average turnover-rate increases from 0.79 to 1.11 in our sample, while the fee burden remains pretty constant at about 1.80% p.a. The mean number of funds a specific fund is competing against in its family (segment) is 40 (341). These two numbers steadily increase from 1993 to 2001, which is also an indication for the growth of the fund market in general.

4 Results

4.1 Influence of Previous Year's Flows

The results from our estimation of model (2) are presented in Table 2.

+ + + PLEASE INSERT TABLE 2 ABOUT HERE + + +

The influence of $FLOW_{i,t-1}$ on $FLOW_{i,t}$ is positive and statistically significant at the 1%-level. This effect is also economically meaningful. The estimated coefficient is 0.1885, i.e. a fund that doubled in size in the previous year is growing by an additional 18.85% in the present year just because of its previous growth. This indicates the existence of a SQB.

The influence of $Perf_{i,t-1}$ is significantly positive, as expected. Investors chase past performance.

Surprisingly, we find a marginally significant positive influence of previous year return risk, $Std_{i,t-1}$, on fund growth. This would contradict the assumption of risk-averse investors that is commonly made. However, this effect might be due to the supposed convexity of the performance-flow relationship: because funds that follow a high risk strategy are more likely to achieve an extreme rank and thereby experience larger expected inflows.[11]

The size of the fund, $lnTNA_{i,t-1}$, has a negative influence on fund growth, i.e. it is easier for smaller funds to grow on a percentage basis than for larger funds. However, there is no significant influence of the age of the fund, $lnAge_{i,t-1}$, on its growth.

The number of other funds offered by the same fund family has a positive impact on fund growth. This indicates that investors put a positive value on the switching option.

Taking the supposed convexity of the performance-flow relationship into account, we still find a positive and significant influence of $FLOW_{i,t-1}$ (see model (3) and (4) in Table 2), confirming the result from model (2). The significantly positive coefficients for the influence of $FLOW^2_{i,t-1}$ (model (3)) and for the coefficients of the piecewise linear regression (model (4)) indicate that the performance flow relationship is clearly convex. This result confirms the findings of earlier studies (see, e.g., Sirri and Tufano (1998)).[12]

The influence of $Std_{i,t-1}$ is not significant in models (3) and (4). The estimates for the other control variables remain very similar. The R^2 of our regressions is between 18.56% and 19.78%. If we estimate models (2) - (4), but leave aside the influence of $FLOW_{i,t-1}$, the R^2's are much lower at about 15% (they are reported for information in Table 2 in the next to last column), i.e. the explanatory power of our models can be increased by nearly a third if we include $FLOW_{i,t-1}$.

4.2 Dependence of the SQB on the number of alternatives

The main contribution of our study is to empirically examine the dependence of the SQB on the number of alternatives. Based on the experimental results in Samuelson and Zeckhauser (1988), we expect the SQB to be stronger if the number of alternatives is larger. We define the number of alternatives as the number of funds offered to investors in the different fund segments. Therefore, we expect the influence of $FLOW_{i,t-1}$ to be stronger, if we look at large segments, as compared to small segments. To examine this hypothesis, we split our sample in 8 subsamples according to segment size: 2-10, 11-25, 26-50, 51-100, 101-200, 201-400, 401-600, and more than 600 alternatives.[13] We estimate models (2) to (4) for each size-class separately. For reasons of brevity we only report the estimates for the influence of $FLOW_{i,t-1}$ on fund growth, which represents the extent to which investors are subject to a SQB. Results are presented in Table 3.

+ + + PLEASE INSERT TABLE 3 ABOUT HERE + + +

Except in the case of 2-10 alternatives, we find significant coefficients in each case.[14] The influence of $FLOW_{i,t-1}$ increases with the number of investment alternatives offered in the segment. This suggests that the extent of the SQB positively depends on the number of alternatives investors can choose from. In the case of 11-25 alternatives, the estimated coefficient is 7.17%, while it is over 18% in the case of 51-100 alternatives and even nearly 24% in the case of 101-200 alternatives, i.e. the SQB is three times as large in the case of more than 100 alternatives as compared to a situation with less than 50 alternatives. The influence of $FLOW_{i,t-1}$ decreases slightly for the cases of more than 200 alternatives, but stays well above 21%.[15]

Overall, we confirm the experimental result of Samuelson and Zeckhauser (1988) using real data from the US mutual fund market. Our results indicate that fund investors are subject to a SQB. The SQB is the stronger the larger the number of alternatives to choose from is.

5 Robustness and Limitations of Results

5.1 Alternative Performance Measures

In the previous section we use ranks based on raw returns as performance measure. However, our results do not depend on the choice of this specific performance measure. In Table 4 we present results of the same estimations as in Table 3, but use ranks based on Sharpe-Ratios and 4-factors alphas (see Carhart (1997)) instead of ranks based on raw returns.

+ + + PLEASE INSERT TABLE 4 ABOUT HERE + + +

Results remain very similar. The SQB is more severe in situations with more alternatives.

5.2 Definition of the Number of Alternatives

We argue, that the relevant number of alternatives a fund investors chooses from is given by the number of funds available in a segment. This is a natural definition, as funds mainly compete against the other funds within the same segment (see, e.g., Navone (2002)). However, one could also imagine that the relevant number of alternatives is given by the overall number of funds in the market (see Section 5.2.1) or by the number of funds offered by one specific fund family (see Section 5.2.2).

5.2.1 Fund universe as relevant number

In this section we assume that the relevant number of alternatives fund investors choose from is given by the total number of all funds in existence in a given year in the whole market. Therefore, we repeat our analysis using all equity funds that are available in our dataset, but examine model (2) for each year of our sample separately. The overall number of funds offered (and thereby the number of alternatives according to the definition in this subsection) steadily increases over time (see Table 1). Therefore, we should see an increase in the influence of $FLOW_{i,t-1}$ on $FLOW_{i,t}$ over time, if the total number of funds is actually the relevant number of alternatives. To examine this, we use two specifications: (a) segment ranks based on raw returns are used as performance measure. (b) the raw return of the funds is used as performance measure.[16] In (a) we assume, that funds compete against each other for inflows via their relative position within their segment, although the total number of funds on the market is the relevant number of alternatives for investors. In contrast, in (b) we assume, that all funds from all segments directly compete against each other, based on their raw returns. Results for both specifications are presented in Table 5.

+ + + PLEASE INSERT TABLE 5 ABOUT HERE + + +

For the whole sample period (last row) the coefficient for the influence of $FLOW_{i,t-1}$ is between 18% and 19% (dependent on the specification) and is statistically significant at the 1%-level. The R^2 (not reported) for specification (b) is always about one third lower than for the regressions using specification (a). This indicates, that inflows can be better explained by the relative position of a fund in its segment than by its raw return.

We find no clear trend over time with respect to the extent of the SQB (see Table 5). The coefficient for the influence of $FLOW_{i,t-1}$ varies over time, but there is no clear pattern. If the number of funds available in the whole market would be the relevant number of alternatives, we should see an increase in the influence of $FLOW_{i,t-1}$ over time, because the number of funds steadily increases (see Table 1). Our result suggests, that there is no influence of the total number of funds available on the extent of the SQB.

5.2.2 Funds in the family as relevant number of alternatives

Instead of looking at the number of funds offered in specific segments or the whole market, one can also argue that the number of funds offered by a family is the relevant number of alternatives for investors. Similar as in Section 5.2.1, we use two specifications, to examine this effect: (a) We use the segment rank of a fund as performance measure. (b) We use the relative return rank of a fund in its family as performance measure.Thereby we implicitly assume that only the funds of a family compete against each other. In both cases we split up our sample with respect to the number of funds in the family. Similar as above, we define classes with respect to the number of alternatives in the family: 2-10, 11-25, 26-50, 51-100, and more than 100 funds. Except of the last class (1.514 observations), this results in similar number of funds of about four to five thousand in each class. Results are presented in Table 6.

+ + + PLEASE INSERT TABLE 6 ABOUT HERE + + +

The influence of $FLOW_{i,t-1}$ is still positive and statistically significant on the 1%-level in all specifications. However, irrespective of which specification we use, we find no clear trend with respect to the extent of the SQB dependent on the number of funds in the family.

Overall, our results suggest that the number of funds offered overall and the number of funds offered within a specific family does not have a systematic influence on the extent of the SQB. The extent of the SQB only depends on the number of funds in the same segment in a systematic way. This result is also consistent with the result of Navone (2002), who reports that funds only directly compete against the other funds in their own segment.

5.3 Controlling for Performance in $t-2$ and $t-3$

Fant and O'Neal (2000) argue that autocorrelation in fund inflows could be due to the fact that investors not only look at the performance in the previous year, but also at the performance in earlier years. In that case, a positive influence of $FLOW_{i,t-1}$ might just expresses the positive influence of a good performance prior to year $t-1$. To control whether this effect has any influence on our results, we extend our base model (2) to include the performance in $t-2$ and $t-3$.[17] The new regression model reads:

$$FLOW_{i,t} = b_1 \cdot FLOW_{i,t-1} + b_{2a} \cdot Perf_{i,t-1} + b_{2a} \cdot Perf_{i,t-2} + b_{2c} \cdot Perf_{i,t-3} + \dots \qquad (5)$$

where the same control variables as in model (2) are included, which are denoted by ... in (5).

Results are very similar as those reported for the estimation of model (2) in Table 2. The influence of the additional performance terms $Perf_{i,t-2}$ and $Perf_{i,t-3}$ is significantly positive. The influence of $FLOW_{i,t-1}$ in this model for different numbers of alternatives in the segment is reported in Table 7.

+ + + PLEASE INSERT TABLE 7 ABOUT HERE + + +

For the whole sample, we find an estimated coefficient of 16.15% for the influence of $FLOW_{i,t-1}$, i.e. the SQB slightly decreases but still clearly persists if we control for the influence of the performance in prior years.[18] We are also able to confirm our finding from above, that the extent of the SQB depends on the number of alternatives. The influence of $FLOW_{i,t-1}$ is more than five times as large if the number of alternatives is 401-600 as compared to the case of 26-50 alternatives.

5.4 Limitations and Possible Caveat

Although our main result of the dependence of the SQB on the number of alternatives is very robust, there are still two possible limitations.

First, we only have aggregate data on the fund-level available. For a more detailed examination we would need time-series data on the decisions of individual investors, which we do not have available. However, our main conclusions can also be derived using the aggregate data we have at hand.

Second, the influence of $FLOW_{i,t-1}$ on $FLOW_{i,t}$ might not be due to a SQB, but due to other fund-specific factors that influence purchase decisions of fund investors and that do not change over time. This should only be a minor problem, as we control for the influence of those variables, that have proven to influence fund growth in previous studies. Moreover, in order to explain our results, these fund specific influences would have to be stronger in large segments than in small segments. We are not aware of any such influences, but can not entirely rule out that they might exist.

6 Conclusion

Individuals are subject to a status quo bias (SQB) if they tend to choose an alternative they chose in a previous decision situation, even if this alternative is not the optimal alternative any more. This anomaly has firstly been documented in an experimental study by Samuelson and Zeckhauser (1988).

Mutual fund investors are also subject to a SQB. Patel et al. (1991) interpret the positive influence of a fund's growth rate on its subsequent growth as evidence for the existence of a SQB. We confirm their result using an extended sample including all US equity mutual funds from 1993-2001. We find a positive influence of previous growth on current growth in mutual fund segments with a large number of funds, but also in small segments of the industry. This influence is very stable and does not depend on the specific model chosen.

The main contribution of this paper is to show empirically that the extent of the SQB in repeated decisions (i.e. where the status quo is given by the previously chosen alternative) strongly depends on the number of alternatives. We argue, that the number of alternatives investors can choose from is given by the number of funds offered in the specific market segment the investor wants to invest in. The greater the number of alternatives offered, the more pronounced the SQB is. The SQB if there are more than 100 alternatives is three times as large as if there are only less than 25 alternatives. This confirms the experimental evidence presented in Samuelson and Zeckhauser (1988) in a real world setting.

Overall, this study contributes to a better understanding of the behavior of mutual fund investors and the biases they are subject to when it comes to making investment decisions.

References

Agarwal, V., Daniel, N. D., & Naik, N. Y. (2004). *Flow, performance and managerial incentives in the hedge fund industry.* (Working Paper)

Agnew, J., Balduzzi, P., & Sunden, A. (2003). Portfolio choice and trading in a large 401(k) plan. *American Economic Review*, *93*, 193-215.

Ameriks, J., & Zeldes, S. D. (2001). *How do household portfolio shares vary with age?* (Working Paper)

Barber, B. M., Odean, T., & Zheng, L. (2004). Out of sight, out of mind: The effects of expenses on mutual fund flows. *Journal of Business*, *forthcoming.*

Barber, B. M., Odean, T., & Zhu, N. (2003). *Systematic noise.* (Working Paper)

Bergstresser, D., & Poterba, J. (2002). Do after-tax returns affect mutual fund inflows? *Journal of Financial Economics*, *63*, 381-414.

Berk, J. B., & Green, R. C. (2004). Mutual fund flows and performance in rational markets. *Journal of Political Economy*, *112*, 1269-1295.

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

Chevalier, J., & Ellison, G. (1997). Risk taking by mutual funds as a response to incentives. *Journal of Political Economy*, *105*, 1167-1200.

DelGuercio, D., & Tkac, P. A. (2002). *Star power: The effect of Morningstar ratings on mutual fund flows.* (Working Paper)

Elton, E. J., Gruber, M. J., & Blake, C. R. (2001). A first look at the accuracy of the CRSP mutual fund database and a comparison of the CRSP and Morningstar mutual fund databases. *Journal of Finance*, *56*, 2415-2430.

Fant, L., & O'Neal, E. S. (2000). Temporal changes in the determinants of mutual fund flows. *Journal of Financial Research*, *23*, 353-371.

Gaspar, J.-M., Massa, M., & Matos, P. (2004). Favoritism in mutual fund families? Evidence on strategic cross-fund subsidization. *Journal of Finance*, *forthcoming*.

Goetzmann, W. N., Massa, M., & Rouwenhorst, K. G. (2000). *Behavioral factors in mutual fund flows.* (Working Paper)

Guedj, I., & Papastaikoudi, J. (2004). *Can mutual fund families affect the performance of their funds?* (Working Paper)

Harless, D. W., & Peterson, S. P. (1998). Investor behavior and the persistence of poorly-performing mutual funds. *Journal of Economic Behavior and Organization*, *37*, 257-276.

Iyengar, S. S., & Lepper, M. R. (2000). When choice is demotivating: Can one desire too much of a good thing? *Journal of Personality and Social Psychology*, *79*, 995-1006.

Kempf, A., & Ruenzi, S. (2004). *Family matters - the performance flow relationship in the mutual fund industry.* (Working Paper)

Khorana, A. (1996). Top management turnover: An empirical investigation of mutual fund managers. *Journal of Financial Economics*, *40*, 403-426.

Khorana, A., & Servaes, H. (2004). *Conflicts of interest and competition in the mutual fund industry.* (Working Paper)

Madrian, B. C., & Shea, D. F. (2001). The power of suggestion: Inertia in 401(k) participation and savings behavior. *Quarterly Journal of Economics*, *116*, 1149-1187.

Navone, M. (2002). *Universal versus segmented competition in the mutual fund industry.* (Working Paper)

Patel, J., Zeckhauser, R., & Hendricks, D. (1991). The rationality sruggle: Illustrations from financial markets. *American Economic Review*, *81*, 232-236.

Patel, J., Zeckhauser, R. J., & Hendricks, D. (1994). Investment flows and performance: Evidence from mutual funds, cross-border investments, and new issues. In R. Sato, R. M. Levich, & R. V. Ramachandran (Eds.), *Japan, Europe, and international financial* *markets: Analytical and empirical perspectives* (p. 51-72). Cambridge (UK): Cambridge University Press.

Ritov, I., & Baron, J. (1992). Status-quo bias and omission bias. *Journal of Risk and Uncertainty*, *5*, 49-61.

Rubaltelli, E., Rubichi, S., Savadori, L., Tedeschi, M., & Ferretti, R. (2005). Numerical information format and investment decisions: Implications for the disposition effect and the status quo bias. *Journal of Behavioral Finance*, *6*, 19-26.

Samuelson, W., & Zeckhauser, R. (1988). Status quo bias in decision making. *Journal of Risk and Uncertainty*, *1*(1), 7-60.

Siggelkow, N. (2003). Why focus? A study of intra-industry focus effects. *Journal of Industrial Economics*, *51*, 121-150.

Sirri, E. R., & Tufano, P. (1998). Costly search and mutual fund flows. *Journal of Finance*, *53*, 1589-1622.

Smith, K. V. (1978). Is fund growth related to fund performance? *Journal of Portfolio Management*, *5*, 49-54.

Spitz, A. E. (1970). Mutual fund performance and cash inflow. *Applied Economics*, *2*, 141-145.

Woerheide, W. (1982). Investor response to suggested criteria for the selection of mutual funds. *Journal of Financial and Quantitative Analysis*, *17*, 129-137.

Notes

[1]As we focus on repeated decision situations, we define the status quo as the alternative that an individual chose in a previous decision situation. Some papers also define an exogenous alternative as status quo, although the individual did not actively opt for it. Our definition of status quo allows us to concentrate on active decisions made by investors, thereby avoiding the possible mix up of the SQB and the omission bias (see Ritov and Baron (1992)).

[2]Rubaltelli, Rubichi, Savadori, Tedeschi, and Ferretti (2005) also present experimental evidence, that fund investors are subject to the SQB. They show that the way in which information on past returns is presented influences the extent of the SQB.

[3]There is a related stream of literature that looks at the influence of the number of alternatives on participation and choice behavior (Iyengar and Lepper (2000) and Madrian and Shea (2001)). These studies find that individuals' tendency to opt for a exogenously proposed choice increases with the number of alternatives offered. However, these studies do not look at repeated decisions, where the SQB is given by the alternative chosen in the first decision.

[4]A segment is defined as the entirety of all funds having comparable investment objectives, e.g., Growth, Growth & Income, or Health Sector funds.

[5]A fund family is defined as the entirety of all funds managed by the same fund management company, e.g. Janus or Fidelity.

[6]Results do not hinge on these assumptions (see Sirri and Tufano (1998)).

[7]Our main results do not hinge on the choice of return ranks as performance measure (see Section 5.1).

[8]Barber et al. (2004) report an average holding period of only 30 months. Therefore, we also do our examinations setting $Fees_{i,t} = Expenses + (1/2.5) \cdot Loads$. Our results are not affected by this.

[9]Splitting up the performance ranks to allow for five (instead of three) different slope coefficients does not affect our results.

[10]Source: CRSP^{TM}, Center for Research in Security Prices. Graduate School of Business, The University of Chicago. Used with permission. All rights reserved. crsp.uchicago.edu. For a more detailed description of the CRSP database, see Carhart (1997) and Elton, Gruber, and Blake (2001).

[11]The significant influence of $Std_{i,t-1}$ actually vanishes if we model a convex relationship between fund growth and prior performance (Models (3) and (4) in Table 2.).

[12]Note, that the existence of a convex relationship between $FLOW_{i,t}$ and $Perf_{i,t-1}$ can also be explained by the existence of a SQB. If investors that already invested some money in the mutual fund market do not change their investments and new investors buy the last year's best performers, this results in a convex performance flow relationship. However, there are also other theoretical arguments that explain a convex performance flow relationship (see, e.g., Berk and Green (2004)). We will therefore concentrate our arguments with respect to the SQB on the influence of $FLOW_{i,t-1}$ on $FLOW_{i,t}$.

[13]We also analyze alternative split-ups. Our results are not substantially affected by this.

[14]The positive but insignificant coefficient for the 2-10 case is due to small number of observations.

[15]This might be due to the fact that some investors use classifications other than the SI-objective classification, that further divide our largest segments into finer sub-segments.

[16]We also examine market-wide fractional ranks based on returns. Results do not change.

[17]There is no significant influence of the performance in years before $t-3$.

[18]We also test specifications allowing for a convex influence of $Perf_{i,t-2}$ and $Perf_{i,t-3}$. Results (not reported here) are very similar.

Table 1: Descriptive Statistics

This table contains summary statistics of our data sample. The second column contains the number of observations and the third column contains the mean total net asset under management (TNA) of the funds in million USD. Column 4 presents the average growth rate of the funds. The average age of all funds in a given year and for the whole period in years is presented in column 5. Column 6 and 7 contain the mean turnover rate and the mean fee burden, which are in % p.a. and are computed as the sum of 1/7th of the load fees plus the years expense ratio. The last two columns contain the average number of competitors a fund has within its family and within its segment, respectively.

							Mean Number of Competitors	
Year	Number	TNA	FLOW	Age	Turnover	Fees	in Family	in Segment
1993	936	646	41,67%	13,81	0,79	1,80%	15	139
1994	1.078	644	15,21%	13,29	0,79	1,73%	15	124
1995	1.036	779	16,64%	12,11	0,79	1,70%	17	151
1996	1.304	786	22,22%	10,32	0,85	1,70%	22	192
1997	1.777	776	25,83%	9,04	0,86	1,75%	33	233
1998	2.437	790	15,87%	8,64	0,89	1,82%	39	272
1999	3.555	804	19,91%	8,32	0,91	1,83%	44	414
2000	3.751	693	18,95%	8,18	1,01	1,83%	46	414
2001	4.319	537	14,16%	8,14	1,11	1,83%	53	488
1993-2001	20.193	709	19,26%	9,14	0,94	1,79%	39	341

Table 2: Influence of Past Growth on Present Growth

This table contains estimation results from models (2) - (4) from the main text for all observations from 1993-2001. Return ranks are used as performance measure. The R^2's of the regressions are presented in the next to last row. The R^2's of respective regressions where the influence of $FLOW_{i,t-1}$ is neglected are presented in the last row. The number of observations in all models is 20.193. ***,**, and * denote statistical significance at the 1%, 5%, and 10%-level respectively.

	Model (2)	Model (3)	Model (4)
$FLOW_{i,t-1}$	0.1885^{***}	0.1845^{***}	0.1807^{***}
$Perf_{i,t-1}$	0.6126^{***}	-0.1938^{***}	-
$Perf_{i,t-1}^2$	-	0.8107^{***}	-
LOW	-	-	0.3790^{***}
MED	-	-	0.3970^{***}
$HIGH$	-	-	2.5781^{***}
$Std_{i,t-1}$	0.1096^{*}	0.0313	0.0275
$lnTNA_{i,t-1}$	-0.0681^{***}	-0.0677^{***}	-0.0674^{***}
$lnAge_{i,t-1}$	-0.0082	-0.0093	-0.0107
$Fees_{i,t-1}$	-2.7270^{***}	-3.0004^{***}	-2.9742^{***}
$TO_{i,t-1}$	0.0085^{***}	0.0077^{***}	0.0073^{***}
$FLOW_{i,t}^{Seg}$	0.1257^{***}	0.1271^{***}	0.1274^{***}
$FLOW_{i,t}^{Fam}$	0.0709^{***}	0.0719^{***}	0.0706^{***}
$lnNum^Fam_{i,t-1}$	0.0439^{***}	0.0479^{***}	0.0490^{***}
R^2	18.56%	19.26%	19.78%
R^2 without $FLOW_{i,t-1}$	14.17%	15.07%	15.77%

Table 3: Influence of the Number of Alternatives

This table contains the estimated coefficients for the influence of previous year fund growth, $FLOW_{i,t-1}$, on present fund growth from models (2)-(4) from the main text. Return ranks are used as performance measure. Regressions are estimated for different subsamples, where the whole sample is divided according to the number of funds offered in the segment. All observations from 1993-2001 are used. The number of observations is presented in the last column. ***,**, and * denote statistical significance at the 1%, 5%, and 10%-level respectively.

Alternatives	Model (2)	Model (3)	Model (4)	N
2-10	0.0466	0.0487	0.0496	270
11-25	0.0717***	0.0643**	0.0865***	1000
26-50	0.0893***	0.0875***	0.1030***	1563
51-100	0.1835***	0.1813***	0.1783***	2767
101-200	0.2389***	0.2361***	0.2533***	3136
201-400	0.2140***	0.2076***	0.2298***	4892
401-600	0.2273***	0.2220***	0.2474***	2752
601-infty	0.2228***	0.2214***	0.2358***	3751
whole sample	0.1885***	0.1845***	0.1807***	20.193

Table 4: Alternative Performance Measures

This table contains the estimated coefficients for the influence of previous year fund growth, $FLOW_{i,t-1}$, on present fund growth from models (2)-(4) from the main text. Regressions are estimated for different subsamples, where the whole sample is divided according to the number of funds offered in the segment. All observations from 1993-2001 are used. In Panel A ranks based on Sharpe Ratios are used as performance measure. In Panel B ranks based on 4-factor alphas are used as performance measure. The number of observations is presented in the last column. ***,**, and * denote statistical significance at the 1%, 5%, and 10%-level respectively.

Panel A: Ranks based on Sharpe-Ratios

Alternatives	Model (2)	Model (3)	Model (4)	N
2-10	0.0484	0.0513	0.0515	270
11-25	0.0732***	0.0728**	0.0722***	1000
26-50	0.0916***	0.0899***	0.0866***	1563
51-100	0.1886***	0.1869***	0.1868***	2767
101-200	0.2377***	0.2356***	0.2340***	3136
201-400	0.2171***	0.2124***	0.2081***	4892
400-600	0.2451***	0.2439***	0.2396***	2752
601-infty	0.2186***	0.2168***	0.2116***	3751
whole Sample	0.1917***	0.1892***	0.1867***	20.193

Panel B: Ranks based on 4-factor Alphas

Alternatives	Model (2)	Model (3)	Model (4)	N
2-10	0.0550	0.0573	0.0568	270
11-25	0.0861***	0.0861**	0.0865***	1000
26-50	0.0911***	0.0886***	0.0883***	1563
51-100	0.2028***	0.2027***	0.2010***	2767
101-200	0.2503***	0.2500***	0.2465***	3136
201-400	0.2351***	0.2319***	0.2295***	4892
400-600	0.2412***	0.2383***	0.2366***	2752
601-infty	0.2392***	0.2386***	0.2357***	3751
whole sample	0.2054***	0.2039***	0.2023***	20.193

Table 5: Total number of funds as relevant number of alternatives

This table contains the estimated coefficients for the influence of previous year fund growth, $FLOW_{i,t-1}$, on present fund growth from models (2)-(4) from the main text. Regressions are estimated for each year 1993-2001 separately. In Panel A segment ranks based on returns are used as performance measure. In Panel B raw returns are used as performance measure. The number of observations is presented in the last column. ***,**, and * denote statistical significance at the 1%, 5%, and 10%-level respectively.

	Panel A: Segment Ranks			Panel B: Returns			
	Model (2)	Model (3)	Model (4)	Model (2)	Model (3)	Model (4)	N
1993	0.1737***	0.1765***	0.1676***	0.1882***	0.1870***	0.2035***	936
1994	0.1505***	0.1451***	0.1419***	0.1408***	0.1474***	0.1487***	1.078
1995	0.1887***	0.1844***	0.1821***	0.1814***	0.1753***	0.1842***	1.036
1996	0.1542***	0.1471***	0.1451***	0.1456***	0.1413***	0.1433***	1.304
1997	0.3574***	0.3444***	0.3333***	0.3409***	0.3420***	0.3350***	1.777
1998	0.2047***	0.2028***	0.2013***	0.2099***	0.1982***	0.2000***	2.437
1999	0.3080***	0.3002***	0.2974***	0.2718***	0.2568***	0.2650***	3.555
2000	0.1597***	0.1606***	0.1576***	0.1642***	0.1732***	0.1758***	3.751
2001	0.1340***	0.1331***	0.1292***	0.1228***	0.1248***	0.1313***	4.319
1993-2001	0.1885***	0.1845***	0.1807***	0.1856***	0.1906***	0.1910***	20.193

Table 6: Total number of funds as relevant number of alternatives

This table contains the estimated coefficients for the influence of previous year fund growth, $FLOW_{i,t-1}$, on present fund growth from models (2)-(4) from the main text. Regressions are estimated for different subsamples, where the whole sample is divided according to the number of funds offered in the family. All observations from 1993-2001 are used. In Panel A segment ranks based on raw returns are used as performance measure. In Panel B family ranks based on raw returns are used as performance measure. The number of observations is presented in the last column. ***,**, and * denote statistical significance at the 1%, 5%, and 10%-level respectively.

	Panel A: Segment Ranks			Panel B: Family Ranks			
	Model (2)	Model (3)	Model (4)	Model (2)	Model (3)	Model (4)	N
2-10	0.1666***	0.1630***	0.1586***	0.1896***	0.1884***	0.1882***	5.253
11-25	0.2291***	0.2226***	0.2157***	0.2447***	0.2426***	0.2427***	4.338
26-50	0.2053***	0.2014***	0.1977***	0.2057***	0.2049***	0.2040***	4.386
51-100	0.1761***	0.1731***	0.1708***	0.1752***	0.1730***	0.1716***	4.702
101	0.1085***	0.1068***	0.1068***	0.0798***	0.0715***	0.0689***	1.514
whole sample	0.1885***	0.1845***	0.1807***	0.2009***	0.1990***	0.1995***	20.193

Table 7: Influence of $FLOW_{i,t-1}$ if prior years' performance is included

This table contains the estimated coefficients for the influence of previous year fund growth, $FLOW_{i,t-1}$, on present fund growth from models (2)-(4) from the main text, where the performance in $t-2$ and $t-3$ are included as additional explanatory variables. All observations from 1993-2001 are used. The number of observations is presented in the next to last column. The R^2's of the regressions are contained in the last column. ***,**, and * denote statistical significance at the 1%, 5%, and 10%-level respectively.

Alternatives	$FLOW_{i,t-1}$	N	R^2
2-10	0,0500	205	21,41%
11-25	0.0197	765	17,97%
26-50	$0,0494^{**}$	1.007	18,96%
51-100	$0,2085^{***}$	1.737	23,97%
101-200	$0,2087^{***}$	1.953	24,17%
201-400	$0,1776^{***}$	2.119	22,03%
401-600	$0,2660^{***}$	1.655	25,44%
600	$0,2410^{***}$	2.270	26,17%
whole sample	$0,1615^{***}$	12.711	18,92%

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