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

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We examine the extent of the status quo bias (SQB) in a real-world repeated decision situation. Individuals who are subject to the SQB tend to choose an alternative that they chose previously (i.e., their status quo), even if it is no longer the optimal choice. We examine the U.S. equity mutual fund market and find strong evidence of the SQB. Furthermore, the SQB is more severe in segments that have more funds to choose from. Thus, we deliver the first empirical confirmation of the experimental results of Samuelson and Zeckhauser [1988] that the SQB depends positively on the number of alternatives.

Introduction

This paper examines the status quo bias (SQB) in the mutual fund market. We focus on how the extent of the SQB depends on the number of alternatives offered.

Individuals are subject to the SQB if they tend to select a suboptimal alternative simply because it was chosen before.[1] For example, if an investor buys a low-performing stock just because she did so previously, that would illustrate the SQB.

It is well documented in the literature that individuals are subject to the SQB when making financial decisions. Samuelson and Zeckhauser [1988] examined the pension plan decisions of Harvard employees and found evidence of the SQB. Ameriks and Zeldes [2001] looked at the portfolio holdings of private households, and reported that the composition of their portfolios is rarely and only slightly changed, a result suggesting the presence of the SQB. A similar effect was found by Agnew, Balduzzi, and Sunden [2003], who examined the pension accounts of U.S. investors. Barber, Odean, and Zhu [2006] also report that investors tend to buy stocks they have bought before.

Patel, Zeckhauser, and Hendricks [1991, 1994] have addressed the SQB in the context of purchase decisions of mutual fund investors. They present empirical evidence that fund investors are more likely to buy funds they bought in the past. A similar phenomenon was reported by Agarwal, Daniel, and Naik [2004] for hedge fund investors. These results are also consistent with the idea that fund investors are subject to the SQB.

In an experimental study, Samuelson and Zeckhauser [1988] found that the extent to which individuals are subject to the SQB depends positively on the number of alternatives available.[2] However, to our best knowledge, no empirical evidence from a real-world situation currently documents this.[3] Our study fills this gap by empirically examining how the extent of the SQB in the mutual fund market depends 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: First, mutual funds are a preferred investment vehicle for unsophisticated investors who do not want to directly participate in the stock market. One can argue that behavioral anomalies like the SQB are more important in such retail markets than in markets where the participants are mainly sophisticated specialists.

Second, real-world situations are preferable to experimental situations, because the participating individuals have considerable real money at stake and will therefore be much more careful to act rationally (Samuelson and Zeckhauser [1988]). However, real-world data does of course have one important disadvantage: Many other possible influences may be driving the observed results.

To examine the existence of the SQB in the mutual fund market, we analyze how inflows into a fund depend on previous inflows into the same fund. We examine separately the influence of previous external growth (i.e., growth due to net inflows of new money) for various segments of the mutual fund industry.[4] The number of alternatives for mutual fund investors in each segment is given by the number of funds in that segment. This number varies considerably among different segments, which allows us to examine their in-

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fluence 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 large number of alternatives than in segments with only a small number of alternatives.

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 available alternatives.

Our results contribute to a better understanding of the behavior of mutual fund investors. But 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 more consistent 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 [2006]).

Our results suggest that, ceteris paribus, it is beneficial to push the performance of funds belonging to large 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 consistency of flows. Furthermore, our results can help fund managers (whose salaries depend on the amount of assets they manage (Khorana [1996]) to predict their earnings. An increase due to increased fund growth will be more lasting in larger segments.

The paper is organized as follows: In the second section we introduce our empirical model; the third section presents our data and summary statistics. Section four gives our results. Robustness tests and possible limitations of our results are discussed in the fifth section and the sixth section concludes.

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, because many other variables have been shown 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 they also use other fund-related characteristics. Therefore, we test the following model:

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

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 the second section).

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, which implicitly assumes that all flows occur at the end of the year and that dividends are completely reinvested.[6] Ber and Ruenzi [2006] show that $FLOW_{i,t}$ is a good proxy for actual flows.

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 depends positively on its external growth in the previous year, this indicates its investors are subject to the SQB. However, a positive dependence could also be due to other fund characteristics that do not change over time and that are important determinants of fund investor purchase decisions. Therefore, we must control for these potential influences as well.

It is well-established 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 a performance measure. To calculate these ranks, we sort all funds from a segment according to their raw return, and assign them a rank number 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 the rank number 1. We use return ranks because they can explain fund growth better than cardinal measures, and because returns explain fund growth very well (see, e.g., Patel, Zeckhauser, and Hendricks [1991] and Harless and Peterson [1998]).[7]

The variables contained in Controls are:

$Std_{i,t}$ denotes the annualized standard deviation of fund i's return in t. A negative influence of $Std_{i,t}$ indicates fund investors are risk-averse, and prefer funds with low return volatility. 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 tend to grow more slowly 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 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]).

Note that fees also play an important role in explaining fund growth (Sirri and Tufano [1998], Khorana and Servaes [2004], and Barber, Odean, and Zheng [2005]). We follow the literature and assume an average holding period of seven years (see Sirri and Tufano [1998]). Therefore, we calculate the measure for the fee burden of a fund, $Fees_{i,t}$, by adding the expense ratio of a fund to one-seventh the front-end load.[8]

The turnover rate, $TO_{i,t}$, also potentially influences fund growth. A positive coefficient indicates that investors prefer an active investment style. Bergstresser and Poterba [2002] find a positive influence of trading activity on fund growth. However, Woerheide [1982] finds no significant relationship.

Many families offer investors the opportunity to switch between the family's funds at no cost (see, e.g., Siggelkow [2003]). The value of this switching option depends positively on the number of other funds offered by the same family, so we add the number of other funds offered, $Numb_{i,t}$, as an 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 the fund's family, $FLOW_{i,t}^{Seg}$ 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 [2005], 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 with a value of 1 if an observation is from year t, and 0 otherwise. These dummy variables allow us to control for year-specific effects. We use these dummies because we pool observations from all years into one regression. Note that we include all variables whose values are unknown to investors at the beginning of year t with their $t\text{-}1$ 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 Sirri and Tufano [1998]).

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 from the literature: 1) we add $Perf_{i,t-1}^2$ to our regression (see Barber, Odean, and Zheng [2005]):

$$\begin{aligned} FLOWi,t = {} & b_1 \cdot FLOW_{i,t-1} + b_{2a} \cdot Perf_{i,t-1} \\ & + b_{2b} \cdot Perf_{i,t-1}^2 + b_3 \cdot Std_{i,t-1} \\ & + b_4 \cdot lnTNA_{i,t-1} + b_5 \cdot lnAge_{i,t} \\ & + b_6 \cdot Fees_{i,t-1} + b_7 \cdot TO_{i,t-1} \\ & + b_8 \cdot FLOW_{i,t}^{Seg} + b_9 \cdot FLOW_{i,t}^{Fam} \\ & + b_{10} \cdot lnNumb_{i,t-1}^{Fam} \\ & + \sum_{j=1993}^{2001} a_j \cdot D_j, \end{aligned} \tag{3}$$

and 2) we apply a piecewise linear regression approach (see Sirri and Tufano [1998]). Note that we estimate the slope coefficients for the lowest quintile, the three middle quintiles, and the top quintile of the fractional performance separately.

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

where

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

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 given by b_{low}.[9]

Data and Summary Statistics

We use data from the CRSP survivor bias-free mutual fund database,[10] which contains data on monthly total returns, fund management company, year of origin, and other fund characteristics. To define which market segments mutual funds belong to, we use the Strategic Insight Objectives (SI) fund classification provided in the CRSP database. Because it is only available from 1993, our study begins there, and it ends in 2001, which leaves us with nine years of data. We exclude all bond and money market funds, and 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 grew by more than 500%. Overall, our sample contains 20,193 yearly fund observations from 38 different segments and 383 different fund families. An overview is given in Table 1.

The number of funds in our dataset grew more than fourfold during our sample period, from 936 in 1993 to 4,319 in 2001. The average fund in our dataset manages more than U.S. $700 million. The average growth rate (*FLOW*) of all funds is nearly 20% per year, however, in 1993, it was much higher, at nearly 40%. The average age of a fund is nine years, but it steadily declines from nearly fourteen years in 1993, to only about eight years in 2001. This trend is due to the emergence of a large number of new funds in the late 1990s.

The average turnover rate in our sample ranges from 0.79 to 1.11, while the fee burden remains fairly constant at about 1.80% per year. The mean number of funds that a specific fund competes against in its family (segment) is 40 (341). These two numbers steadily increase from 1993 to 2001, which is also an indication of the growth of the fund market in general.

Results

Influence of Previous Year's Flows

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

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 the previous year is growing by an additional 18.85% the present year just because of its previous growth. This indicates the existence of the SQB. The influence of $Perf_{i,t-1}$ is significantly positive, as expected, because investors tend to 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 common assumption that investors are risk-averse. However, this effect might be due to the supposed convexity of the performance flow relationship. Funds that follow a high-risk strategy are more likely to achieve an extreme rank, and therefore more likely to 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 it is for larger funds. However, we find 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 place a positive value on the switching option.

Table 1. *Descriptive Statistics*

							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

Note: This table contains summary statistics for our data sample. The second column contains the number of observations, and the third column contains the mean total net assets under management (TNA) of the funds in $U.S. million. Column 4 gives the average growth rate of the funds. Column 5 gives the average age of all funds in a given year and for the whole period in years. Columns 6 and 7 contain the mean turnover rate and the mean fee burden, respectively, which are in % per year and are computed as the sum of one-seventh of the load fees plus the year's expense ratio. The last two columns contain the average number of competitors a fund has within its family and within its segment, respectively.

Table 2. *Influence of Past Growth on Present Growth*

	Model (2)	Model (3)	Model (4)
$FLOW_{i,t-1}$	0.1885***	0.1845***	0.1807***
$Perf_{i,t-1}$	0.6126***	–0.1938***	—
$Perf^2_{i,t-1}$	—	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***
$FLOW^{Seg}_{i,t}$	0.1257***	0.1271***	0.1274***
$Flow^{Fam}_{i,t}$	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%

Note: This table contains estimation results from models (2)–(4) from the main text for all observations from 1993–2001. Return ranks are used as the performance measure. The R^2s of the regressions are presented in the next to last row. The R^2s 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% levels, respectively.

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 models (3) and (4) in Table 2), which confirms the results 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), and 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^2s are much lower, at about 15% (see the next to last column in Table 2). In other words, the explanatory power of our models can be increased by nearly one-third if we include $FLOW_{i,t-1}$.

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 available 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 than if we look at small segments.

To examine this hypothesis, we split our sample into eight 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)-(4) for each class size 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 the SQB. Results are in Table 3.

We find significant coefficients in each case, except for the case of 2–10 alternatives.[14] The influence of $FLOW_{i,t-1}$ increases with the number of available investment alternatives, which suggests that the extent of the SQB depends positively on the number of alternatives. For 11–25 alternatives, the estimated coefficient is 7.17%, for 51–100, it is over 18%, and for 101–200, it is nearly 24%, i.e., the SQB is three times as large for more than 100 alternatives than for less than 50 alternatives. The influence of $FLOW_{i,t-1}$ decreases slightly for more than 200 alternatives, but it stays well above 21%.[15]

Overall, we confirm the experimental results of Samuelson and Zeckhauser [1988], using real data from the U.S. mutual fund market. Our results indicate that fund investors are subject to the SQB, and it becomes stronger the larger the number of alternatives.

Robustness and Limitations of Results

Alternative Performance Measures

In the previous section, we used ranks based on raw returns as a performance measure. However, our results do not depend on this specific performance mea-

Table 3. *Influence of the Number of Alternatives*

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***	1,000
26–50	0.0893***	0.0875***	0.1030***	1,563
51–100	0.1835***	0.1813***	0.1783***	2,767
101–200	0.2389***	0.2361***	0.2533***	3,136
201–400	0.2140***	0.2076***	0.2298***	4,892
401–600	0.2273***	0.2220***	0.2474***	2,752
601–infty	0.2228***	0.2214***	0.2358***	3,751
Whole Sample	0.1885***	0.1845***	0.1807***	20,193

Note: This table contains the estimated coefficients for the influence of previous-year fund growth, $FLOW_{i,t-1}$, on present-year fund growth from models (2)–(4) from the main text. Return ranks are used as the 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% levels, respectively.

sure. In Table 4, we use ranks based on Sharpe ratios and four-factor alphas (see Carhart [1997]), and present results for the same estimations as in Table 3.

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

Definition of the Number of Alternatives

We argue that the relevant number of alternatives available to a fund investor is given by the number of funds available in a segment. This is a natural definition, as funds mainly compete against other funds within the same segment (see, e.g., Navone [2002]). However, the relevant number of alternatives could also be given by the overall number of funds in the market, or by the number of funds offered by one specific fund family.

Fund Universe as Relevant Number

In this section, we assume that the number of available alternatives is the total number of all funds

Table 4. *Alternative Performance Measures*

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***	1,000
26–50	0.0916***	0.0899***	0.0866***	1,563
51–100	0.1886***	0.1869***	0.1868***	2,767
101–200	0.2377***	0.2356***	0.2340***	3,136
201–400	0.2171***	0.2124***	0.2081***	4,892
400–600	0.2451***	0.2439***	0.2396***	2,752
601–infty	0.2186***	0.2168***	0.2116***	3,751
Whole Sample	0.1917***	0.1892***	0.1867***	20,193

Panel B. Ranks Based on Four-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***	1,000
26–50	0.0911***	0.0886***	0.0883***	1,563
51–100	0.2028***	0.2027***	0.2010***	2,767
101–200	0.2503***	0.2500***	0.2465***	3,136
201–400	0.2351***	0.2319***	0.2295***	4,892
400–600	0.2412***	0.2383***	0.2366***	2,752
601–infty	0.2392***	0.2386***	0.2357***	3,751
Whole Sample	0.2054***	0.2039***	0.2023***	20,193

Note: This table contains the estimated coefficients for the influence of previous-year fund growth, $FLOW_{i,t-1}$, on present-year 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 the performance measure. In Panel B, ranks based on four-factor alphas are used. The number of observations is presented in the last column. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

in existence in a given year in the entire market. Therefore, we repeat our analysis using all available equity funds in our dataset, but examine model (2) separately for each year of our sample.

We find that the overall number of funds offered 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. To examine this, we use two performance measures: 1) segment ranks based on raw returns, and 2) the raw returns of the funds.[16] In (1), we assume that funds compete against each other for inflows via their relative position within their segment (even though the total number of funds on the market is the relevant number of alternatives for investors). In contrast, in (2) we assume that all funds from all segments directly compete against each other, based on their raw returns. Results for both specifications are in Table 5.

For the whole sample period (last row), the coefficient for the influence of $FLOW_{i,t-1}$ is between 18% and 19% (depending on the specification), and is statistically significant at the 1% level. The R^2 (not reported) for specification (2) is always about one-third lower than that for specification (1). 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 entire market were indeed the relevant number of alternatives, we would expect to see an increase in the influence of $FLOW_{i,t-1}$ over time, because the number of funds steadily increases (see Table 1). Our results suggest there is no influence of the total number of funds available on the extent of the SQB.

Funds in the Family as Relevant Number

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. We use two specifications to examine this effect: 1) the segment rank of a fund, and 2) the relative return rank of a fund in its family. Thus, 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. And we again 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 for the last class (1,514 observations), this results in about 4,000–5,000 funds in each class. Results are in Table 6.

The influence of $FLOW_{i,t-1}$ is still positive and statistically significant at the 1% level in all specifications. However, no matter which specification is used, there is no clear evidence that the extent of the SQB depends 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 do not systematically influence the extent of the SQB. The extent of the SQB appears to depend only on the number of funds in the same segment. This result is consistent with Navone [2002], who reports that funds only directly compete against other funds in their own segment.

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 consider prior years' performance as well as previous-year performance. In that case, a positive influence

Table 5. *Total Number of Funds as Relevant Number of Alternatives*

	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

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

Table 6. *Total Number of Funds as Relevant Number of Alternatives*

	Panel A. Panel 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***	5253
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

Note: This table contains the estimated coefficients for the influence of previous-year fund growth, $FLOW_{i,t-1}$, on present-year 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 the performance measure. In Panel B, family ranks based on raw returns are used. The number of observations is presented in the last column. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

of $FLOW_{i,t-1}$ might express the positive influence of a good performance prior to year $t-1$. To control whether this 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 is:

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

where we include the same control variables as in model (2), denoted by …in Equation (5).

Results are very similar to those 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.

For the whole sample, we find an estimated coefficient of 16.15% for the influence of $FLOW_{i,t-1}$, i.e., the SQB decreases slightly but still clearly persists if we control for the influence of prior-year performance.[18] We also confirm our finding 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 when the number of alternatives is 401–600 than when it is 26–50.

Table 7. *Influence of $FLOW_{i,t-1}$ if Prior Years' Performance Is Included*

Alternatives	$FLOW_{i,t-1}$	N	R^2
02–10	0.05	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%

Note: This table contains the estimated coefficients for the influence of previous-year fund growth, $FLOW_{i,t-1}$, on present-year 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^2s of the regressions are contained in the last column. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Limitations and Possible Caveat

Our main result, that the SQB depends on the number of alternatives, is very robust, but 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. 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 the SQB, but rather to other fund-specific factors that influence fund investor purchase decisions and do not change over time. This should only be a minor problem, however, as we control for the influence of 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 larger segments than in smaller segments. We are not aware of any such influences, but cannot entirely rule out their existence.

Conclusion

Individuals are subject to the status quo bias (SQB) if they tend to choose an alternative they chose in a previous decision situation, even if it is no longer the optimal choice. This anomaly was first documented in an experimental study by Samuelson and Zeckhauser [1988].

Mutual fund investors are also subject to the SQB. Patel, Zeckhauser, and Hendricks [1991] interpret the positive influence of a fund's growth rate on its subsequent growth as evidence of the SQB. We confirm their results using an extended sample that includes all U.S. 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 smaller segments of the industry. This influence is very stable and does not depend on the specific model chosen.

Our main contribution 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 available alternatives. We argue that the number of alternatives available to investors is given by the number of funds offered in the specific market segment the investor is interested in. The greater the number of alternatives, the more pronounced the SQB. If there are more than 100 alternatives, the SQB is three times as large as if there are only 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.

Notes

1. Because 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 the status quo, even though the individual did not actively choose it. Our definition allows us to concentrate on active investor decisions, thereby avoiding the possible mix-up of the SQB and the omission bias (see Ritov and Baron [1992]).
2. Rubaltelli et al. [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 its extent.
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 an exogenously proposed choice increases with the number of alternatives offered. However, these studies do not consider repeated decisions.
4. A segment is defined as the entirety of all funds with comparable investment objectives, e.g., Growth, Growth & Income, or Health Sector.
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. Our 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 the performance measure.
8. Barber, Odean, and Zheng [2005] report an average holding period of only thirty months. Therefore, we also perform our examinations setting $Fees_{i,t} = Expenses + (1/2.5) \cdot Loads$. Our results are not affected by this.
9. Splitting the performance ranks to allow for five (instead of three) different slope coefficients does not affect our results.
10. Source: CRSPTM, 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 the SQB. If investors who have already invested in the mutual fund market do not change their investments, and if new investors buy last year's best performers, this results in a convex performance flow relationship. However, other theoretical arguments may also explain this relationship (see, e.g., Berk and Green [2004]). We 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 the small number of observations.
15. This may be because some investors use classifications other than the SI objective classification that further divide our largest segments into finer subsegments.
16. We also examine marketwide fractional ranks based on returns. Our 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.

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