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Benchmark Changes Matter: The Case of Mutual Fund Relative Performance

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Abstract: From data on Sweden-registered mutual funds in the period 1999-2004 we construct a data set free of survivorship bias which we use to test the hypotheses that, on average, a) among funds that change benchmarks, the new benchmark selected ex post has a worse performance than the original benchmark, b) benchmark changes are affected by funds' performance relative to their original benchmarks, and c) benchmark changes affect fund flows. Using simple t-, binomial -, and Wilcoxon tests as well as multinomial logit and fixed effects regression models, we find robust evidence for all three hypotheses. This suggests that at least some funds take relative performance into account when changing benchmarks and that these funds face a tradeoff between reputation and presenting a favorable view to investors. In addition, we observe a high frequency of benchmark changes overall: the majority of funds change at least once during the sample period and on average 17 percent of funds change in any given year.

Keywords: mutual funds, relative performance, benchmark change, performance-flow relationship

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I. Introduction

In Sweden, there has been a debate in the media in recent times regarding the notion that fund management firms, most notably the large domestic banks, have misled investors by beautifying fund factsheets and other information material.¹ One main argument has concerned the firms' benchmark selections: since the vast majority of funds are designed to outperform a given passive benchmark portfolio comprised of one or several market indexes, it follows naturally that these funds should also be evaluated in relation to their benchmark. However, in forming these benchmarks, fund managers have often opted for indexes that are not optimal for comparison. The possible benefit of choosing suboptimal indexes is evident: extracting dividends, for instance, would diminish the performance of a stock market index, thereby making a fund's performance relative to this index appear better than it really is². Another practice with the same effect would be to choose a benchmark that does relatively poorly, should there be alternatives.

Figure A 1 in the appendix (page A-8) shows the development of six common indexes of the Stockholm Stock Exchange. Which index should a fund manager of Swedish equity funds choose? As one can see, there are striking differences in returns, making the decision far more important than how it initially might seem. Although this decision does not *ex post* affect the fund's *actual performance*, it does determine its *relative performance*. Compare it to one index, and the fund might have performed well over the period. Compare it to another, and the picture might look very different. In theory, one could maximize this relative performance by choosing the worst-performing benchmark in any given time period, given that the benchmark is appropriate for the targeted market segment.

There are several motives that may drive a desire to report a good relative performance. For instance, there may be reasons related to prestige or career concerns of managers; indeed, some managers might even have performance-based pay schemes. However, it is reasonable to believe that increasing the fund's attractiveness to investors in order to achieve larger money flows to the fund should be the most significant motive. There is a conflict of interest between investors and fund management firms in this respect; investors want the firms to maximize returns, but the firms themselves want to maximize flow in order to increase the firm value. In an already classic paper, Chevalier & Ellison (1997) find that this agency conflict cause firms to alter their risk level (as measured by the standard deviation) in the last quarter of a year

¹ On public television, a documentary was broadcasted regarding the use of benchmarks without dividends (*Uppdrag granskning*, 2008; and Dahlin, 2008a). The issue was also raised in Sweden's largest newspaper (see Eriksson, 2008a). Quite soon after, however, several large banks changed their benchmarks to be constituted of indexes that incorporate dividends (Lindmark, 2008; Nordea, 2008; Swedbank, 2008; and Eriksson, 2008b) and the government proposed a new law that allows the Swedish Financial Supervisory Authority to impose penalties upon fund management firms who mismanage the distribution of information to investors in cases like those described above (Dahlin, 2008b; and Eriksson, 2008c). Subsequent large outflows were observed for the affected large banks (Eriksson, 2008d).

² The Swedish Investment Fund Association (2000) defends the use of non-dividend indexes by stating that funds have costs whereas an index does not, and hence a fund holding the same securities as an index would not yield the same net returns. However, we find this argument misplaced since extracting dividends can by no means compensate for these fees.

depending on the return in the previous three quarters. In a similar manner, it is possible that fund managers change benchmarks depending on fund performance. For instance, in times of poor performance, the temptation of changing to an easier benchmark may be larger.

The aim of this paper is threefold. First, we examine the direction of benchmark change to spot evidence in favor of the hypothesis that funds change to more poorly performing benchmarks on average. Secondly, we investigate whether fund characteristics affect these changes, and especially if funds' relative performance influences the change decision. Thirdly, we look at the effect on flow, namely whether funds engaging in this practice obtain higher flow.

In a data set consisting of yearly data on Swedish mutual funds in the period 1999-2004, from which benchmark changes attributed to changes in strategy are excluded, we find that the average new benchmark has a statistically significant lower mean and median return compared to the old benchmarks. Furthermore, there is a larger frequency of funds that change to a benchmark with a lower return ("easier") as opposed to funds that change to a benchmark with a higher return ("harder"); the figures are 127 and 86 funds respectively and statistical significant with a binomial test. Split up by performance, sixty percent of benchmark-changing funds (hereafter referred to as "changers") that underperform their benchmark in a given year change to an easier benchmark, whereas the opposite is true for changers that outperform their benchmark. We also observe that for every single year, equity funds that change to easier benchmarks have a substantially lower mean excess return (over their original benchmarks) than those that change to harder benchmarks, and the groups of changers to easier and harder benchmarks differ in terms of fund characteristics. More specifically, a multinomial logit model tells us that a weaker relative performance significantly increases the probability of change to an easier benchmark, whereas the opposite is true for changes to harder benchmarks. Other factors influencing the frequency and direction of benchmark change include fund age, fees, ethical screening, and whether the fund belongs to one of the four main banks in Sweden. An estimated fixed effects regression model gives further evidence and quantifies the relationship: for a fund changing benchmarks, everything else equal, if the excess return over the fund's old benchmark decreases by 1 percent, on average, the fund chooses a new benchmark that is 0.3 percentage points lower relative to what it would have chosen otherwise. Finally, by employing a model taking into account the convex performance-flow relationship, we surprisingly find that changes in both directions affect flow positively; however, this appears to depend on the performance ranking of the fund.

Despite the vast finance literature on mutual funds, not much has been written previously on this particular subject. In fact, there exists no comparable published study to our knowledge. This paper accordingly makes a unique contribution to the mutual fund research literature by investigating the practice of benchmark change, and in addition provides new insights on the flow-performance relationship. The study is hence of relevance to academics as well as to all fund investors and practitioners in the fund management industry. Apart from bringing the side-effect of a potential strategy for fund managers yet unenlightened on the subject, in particular, this paper sheds a light on the ambiguity problem in benchmark comparisons and thereby provides scope for the common investor to become more aware of the importance of proper and thorough comparison when evaluating investment ideas.

II. Theory & Methodology

The fact that the important issue of benchmark choice is hardly or not at all discussed in finance academia can be attributed to the standard view that mutual fund benchmarks are chosen with respect to the funds' strategy and investment objectives and hence not subject to scrutiny. However, in line with the news on dividends extraction and the high propensity of funds to change benchmarks³, we argue that the typical static and straightforward treatment of the benchmark is overly simplistic. Indeed, these two aspects indicate that there may be distinct forces influencing the benchmark selection process. The keystone of our theory is that there is a consideration of the performance of the benchmark in this process. Everything else equal, a benchmark with a high return is less desirable than a benchmark with a low return since the higher return has the effect of making the performance of the corresponding fund come out less favorably. Based on common knowledge and our own experience in the industry, in order for investors to invest in a fund, they need to be convinced of the capacity of the fund manager(s) to generate superior returns – this will not be easy if the fund does not manage to beat its own benchmark. In fact, should they not be able to outperform their benchmark – which academics have found is the case for the majority of funds (the first study being that of Jensen, 1969; see Zheng, 1999, for a discussion) – then clearly investors would be better off placing their money on the benchmark, which these days in many instances can be replicated cheaply by passive index funds and exchange-traded funds (ETFs).

Following this argument, one could think that funds should change to the benchmark that has the lowest return possible. Yet, this extreme case is clearly not realistic since the benchmark must also serve the cause of being a representative comparison to the fund, and thereby exhibit a somewhat similar asset composition. For example, the benchmark should if possible encompass the same geographical market(s) and asset class(es) as the fund and when applicable be limited to a somewhat similar market segment. Deviating too much from such an appropriate benchmark could be met with suspicion among investors. Apart from triggering distrust among informed or sophisticated investors, it carries the risk of unpleasant media coverage – as we have seen proof of during the last few months in Sweden (see Section I). This in turn may have disastrous effects on reputation and accordingly result in long-term negative effects on flow. In contrast, using a tough-to-beat but fair benchmark (which for equity funds can be for example a benchmark that includes dividends) may have a positive effect on reputation.

In other words, changing to a more poorly performing benchmark has both positive and negative potential effects. With this in mind, one could see the problem facing fund managers or the benchmark decision-makers as a dilemma between a) choosing a true representative benchmark that matches the fund better than any other benchmark, and b) choosing a benchmark that makes the fund look good. At any given point in time, there should be a tradeoff between these two objectives. We say “at any given point in time” because the importance of these two objectives ought to vary over funds and time depending on fund characteristics such as performance. For example, a fund that performs miserably in one year

³ In our sample, on average 18 percent of equity funds and 17 percent of all funds change their benchmark at least once in any given year.

might find alternative b) relatively more tempting than a well-performing fund in the same year. Hypothetically, this poorly performing fund might change to an easier benchmark in that year; then a couple of years later, it may find itself on top of the market and switch back to a more representative benchmark in order to avoid the downside risks described earlier.

Figure 1 shows a schematic timeline of our theory on the benchmark change decision process and its relation to performance and flow. At time t , the fund compiles a factsheet where the return history for the fund and its benchmark is reported. Prior to the release of the factsheet, a fund manager notices that his or her fund is underperforming its benchmark. Therefore, the benchmark is changed to a worse-performing benchmark, which we refer to as the new benchmark. Through this change, the relative performance of the past period $t-1$ to t is improved ex post; the excess return over the old benchmark (ex_return_{old}) is negative, whereas the excess return over the new benchmark (ex_return_{new}) is positive.

After observing information in the factsheets, investors decide to buy or sell the fund at time $t+1$. Since only the new benchmark is reported in the factsheet, their investment decision is based on the performance of a fund in relation to its new benchmark, measured by ex_return_{new} .

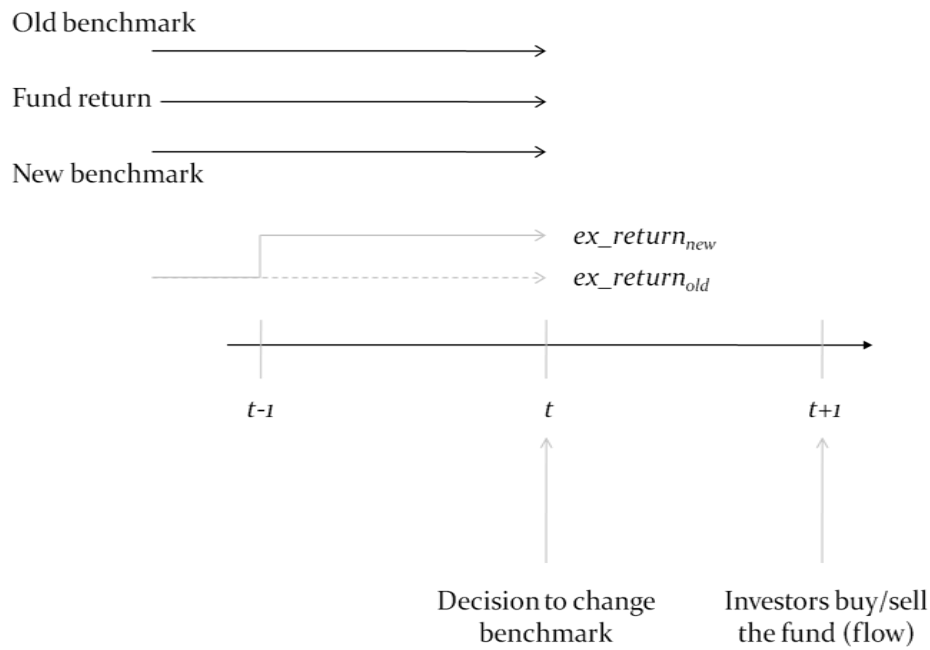


Figure 1. Timeline for Theoretical Framework

This figure shows the theoretical relationship between benchmark change, performance, and flow. At time t funds observe the relative performance measured between $t-1$ and t by the excess return ex_return_{old} . Dependent on this variable, a decision whether a) not to change or b) change to an easier (lower return) or c) harder (higher return) benchmark is taken. This decision results in a new relative performance measure, ex_return_{new} , based on the new benchmark chosen (if no change occurs $ex_return_{new} = ex_return_{old}$). Investors observe and base their investment decisions at time $t+1$ on the presented ex_return_{new} .

The relevant decision facing fund managers at any point in time could be seen as a one-step decision tree with three options: change to an easier benchmark, not change, and change to a harder benchmark. Alternatively, the decision could be seen as a two-step process with an initial decision on whether to change or not, and a secondary decision on whether to change to an easier or harder benchmark. The second decision tree could be seen as more feasible in

cases where the benchmark change is forced upon the fund and/or in cases where no considerations are made of the performance characteristics of the new benchmark – in these cases, the second step in the very same decision tree can be seen as unplanned and the outcomes should accordingly be randomly distributed over changes to easier and harder benchmarks. In effect, our theory does not assume that all funds take performance into account during benchmark changes; naturally, changes can occur for several reasons. Sometimes, benchmark changes follow an outspoken change in strategy that leads to a transformation of the fund's asset composition. Other times, this change has other causes, which typically, according to our observations, are not shared with investors. However, it is still reasonable that for at least some funds, a consideration of the two conflicting objectives regarding appropriateness and fund performance influence benchmark change decisions.

In the example above which constitutes our theoretical framework, we assumed that investors consult factsheets to make their investment decisions. However, naturally, the performances of funds and their benchmarks are reported in many places on various information material made available by the corresponding fund management firms. It does not necessary have to be documents and reports; fund performance is also presented on websites and through advertising. It is realistic to believe that at least some investors and fund managers care about what is reported in these places.

To simplify our analysis, we look at yearly data. Accordingly, we assume that benchmark changes take place at year end and that fund managers are able to observe all characteristics of their funds at any point of time. As a consequence, decisions to change benchmarks are based on fund characteristics at the end of the same year, which has the statistical implication that no lags are needed of the variables in the analyses. One exception is flow, which in line with standard academic practice is assumed to depend on characteristics present one year earlier. We also limit our analysis to benchmark considerations *ex post*, that is, we do not consider the implications of benchmark changes for future relative performance.

A. Hypotheses

We want to examine the benchmark change process statistically. For this inspection, we have three questions in mind. Firstly, do patterns observed in data support the theory that there exist funds that change benchmarks in order to present a more favorable view to investors? Secondly, should this be the case, is this driven by the performance of the funds? Thirdly, is this practice effective in generating higher fund flows? Based on these three questions, we form three corresponding hypotheses. We find empirical evidence for our hypotheses by employing different statistical methods specifically adapted to the hypothesis for which they are used.

Hypothesis 1: On Average, Funds Change to Easier Benchmarks

If in a given year, a mutual fund's benchmark performed strongly in comparison to alternatives, there is an incentive in line with the theory described above to change benchmarks to one of the alternatives. Hence, we expect the majority of funds that change benchmarks to change to an easier (that is, a more poorly performing benchmark), as opposed to an equal amount of changes to harder and easier benchmarks. We test this hypothesis with

parametric and non-parametric tests that compare the returns of old benchmarks with the returns of new benchmarks, as well as the frequency of changes to easier benchmarks with the frequency of changes to harder ones.

Hypothesis 2: The Relative Performance Influences the Change Decision

Since the benefits of change vary, the tradeoff between appropriateness and desire to look good is likely to depend on the performance of a fund in relation to its benchmark. To examine this relationship, we compare funds that do not change benchmarks with funds that change to easier and harder benchmarks, respectively. Furthermore, we develop a multinomial logit model based on the three-option decision tree and investigate determinants of the magnitude of change with a fixed effects model.

Hypothesis 3: Changing Benchmarks has an Impact on Flow

Increasing flow should be the main objective of unforced benchmark adjustments. Since many customers relate the performance of a fund to a benchmark in forming their investment decision (see e.g. Capon, Fitzsimons, and Prince, 1996, and The Swedish Investment Fund Association, 2006) and academics have found a persistent relationship between performance and flows, we expect flows to be affected by benchmark changes. We test this hypothesis by estimating a fixed effects model with various configurations.

B. Definitions & Variables

1. Benchmark Change

In the data gathering process, we assign each unique benchmark an identification number based on the benchmark at year end as reported in the fund factsheet; hence no records are made of multiple benchmarks following changes within the same year. We then identify benchmark changes by observing variation in these identification numbers over time for the same fund. In case of a change, the *new benchmark* is defined as the benchmark presented in the factsheet at time t , and the *old benchmark* as the benchmark reported in last year's factsheet at time $t-1$.

Benchmark changes can be analyzed by looking at the frequency, direction, and magnitude of change. With frequency we refer to the number of years which have benchmark changes for a specific fund during our sampling period. With direction of change we mean whether the change has been to an easier or harder benchmark. We define an *easier benchmark* as one that has a lower one-year return and a *harder benchmark* as one that has a higher one-year return, both in comparison to the benchmark the fund would have had if no change had occurred. The magnitude of change is then calculated as the difference between returns of these benchmarks and is denoted $bmdiff$ as in the equation below:

$$bmdiff_{i,t} = return_{new\ benchmark_{i,t}} - return_{old\ benchmark_{i,t}}$$

2. Performance

Given the assumption that changes occur at year end, the one year return comes across as the most appropriate performance measure since this variable contains all additional information regarding performance since the last year's report. We measure the relative performance of a fund by the excess return over the fund's benchmark, which we denote ex_return . This variable is defined as the simple difference in returns between the fund and its benchmark, and is sometimes referred to as the *active return* among academics. There are two variants of this measure; ex_return_{new} is the excess return using the new benchmark reported in the fund's factsheet, whereas ex_return_{old} is the excess return using the old benchmark. The formula for the latter variable is

$$ex_return_{old_{i,t}} = return_{fund_{i,t}} - return_{old\ benchmark_{i,t}}$$

By definition, it then follows that the change in excess return ensuing the benchmark change is

$$\Delta ex_return_{i,t} = ex_return_{new_{i,t}} - ex_return_{old_{i,t}} = -bmdiff_{i,t}$$

Please note that for funds that do not change benchmarks, the old benchmark is equal to the new benchmark and hence $ex_return_{new} = ex_return_{old}$ in this case.

The use of this simple measure of performance is consistent with Chevalier & Ellison (1997) and actual investor behavior; based on a survey of mutual fund purchasers, Capon, Fitzsimons, and Prince (1996) report that only four percent use the more complex alpha or Sharpe measures. We will, however, use Jensen's alpha for robustness checks due to its popularity among finance academics and by the fact that investors might use this measures indirectly e.g. through advice. This risk-adjusted variable, which we denote $alpha$, is calculated yearly on monthly data (similar to Kempf & Ruenzi, 2008) as the intercept in a regression of a market model with the fund's benchmark as independent variable. It, too, comes in two specifications: $alpha_{new}$ is the alpha in relation to the fund's new benchmark, and $alpha_{old}$ using the old. In a similar way, then

$$\Delta alpha_{i,t} \equiv alphadiff_{i,t} = alpha_{new_{i,t}} - alpha_{old_{i,t}}$$

Keep in mind however, that the interpretation of $alphadiff$ is the change in alpha following the benchmark change, and hence in opposite to $bmdiff$ this value is positive for changes to a benchmark that provides a fund with better relative performance (that is, higher alpha).

3. Flow

We use fund flows to measure investments in a fund. Fund flows are defined as net flows, that is, inflows subtracted by outflows. Consistent with the academic consensus in the last decade (see e.g. Huang, Wei, and Yan, 2007, and related papers) we use the following formula to estimate fund flows, where TNA stands for total net asset value:

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1 + return_{fund_{i,t}})}{TNA_{i,t-1}}$$

Although this specification assumes that flows occur at year end and that all dividends are reinvested, it has been proven to closely resemble actual flows (Ber & Ruenzi, 2006). From now on, when referring to flows, we mean flows in percentage of last year's TNA as in the formula

above; unless referring to money flows, by which we mean flows in real terms (the numerator in the fraction above).

4. *Control Variables*

In addition to our main variables, we use various control variables in the regressions in order to isolate the effects caused by the dependent variables of interest. This is a standard practice and many of the control variables we apply in this paper are also used in related empirical research. The most commonly used controls are size, age, turnover, and fees. Practically all authors in the fields of performance persistency and mutual fund flow use these variables as controls (see e.g. Chevalier & Ellison, 1997, 1999a, and 1999b; Sirri & Tufano, 1998; Jain & Wu, 2000; Dahlquist, Engström, and Söderlind, 2000; Chen, Hong, Huang, and Kubik, 2004; Barber, Odean, and Zheng, 2005; Huang, Wei, and Yan, 2007; and Kempf & Ruenzi, 2008). The value of a fund's total net assets (TNA) is the standard measure for fund size. In accordance with the authors mentioned, we use the natural logarithm of this variable ($\ln TNA$) in all regressions. This procedure is also undertaken for the fund age, accordingly denoted $\ln Age$, which we originally calculate from the corresponding starting date reported in the funds' annual factsheets. The turnover ratio, *Turnover*, is a measure of trading activity and is calculated as the minimum of aggregate purchases of securities or aggregate sales of securities, in percent of the fund's average TNA. Clearly, the level of fees is one of the most important characteristics of mutual funds and they have been found to affect flows as well as performance negatively (Carhart, 1997; Sirri & Tufano, 1998; Dahlquist, Engström, and Söderlind, 2000; Zhao, 2005). We use *totalkostnadsandel* (TKA) as measure of total fees charged, which is defined as total fees as a fraction of TNA. The reason that we use this measure as opposed to the total expense ratio, TER (the most commonly used measure of total fees in the USA), is that TKA is more prevalent in Sweden and hence more frequently reported among the funds in our sample. Due to the inclusion of brokerage fees it is also more comprehensive than TER. Nevertheless the correlation between the two in our sample is 98 percent.

In a survey of Swedish investors, a fund's risk level was found to be the most important criteria in purchasing decisions (The Swedish Investment Fund Association, 2006). In accordance with this, many authors in the flow literature include a variable measuring risk level. We use the standard deviation of monthly returns calculated over the two years preceding the observation. This is the most commonly reported risk measure in the factsheets as well as among academics (see e.g. Sirri & Tufano, 1998; Huang, Wei, and Yan, 2007; Korkeamaki, Puttonen, and Smythe, 2007; and Kempf & Ruenzi, 2008). We refer to the variable as *StDev*.

We also apply a few control variables of our own. Ethical funds are quite common in the Swedish market. To see whether these funds differ from others in respect to our results (as is to be expected following the results by Bollen & Cohen, 2005) we include the dummy variable *Ethical* that takes the value one if the fund applies any kind of negative or positive ethical screening. Theoretically, as the name implies, one would imagine ethical funds to be more frequent users of indexes that include dividends and to participate in relative performance manipulation to a lower extent than other funds.

Frye (2001) finds that bank-managed funds are less sensitive to performance, and Korkeamaki, Puttonen, and Smythe (2007) include a bank variable to capture this difference relative to other funds. The Swedish market is to a large extent dominated by four main banks:

Nordea, SEB, Handelsbanken, and Swedbank. As mentioned in Section I, it is these banks that have come under scrutiny for their benchmarking practices. To see whether they differ significantly from other firms, we include the dummy variable *MainBank* that takes the value one if the fund is provided by one of the four main banks.

III. Data

We use a panel data set free of survivorship bias consisting of virtually all Sweden-registered funds available during the period 1999-2004. These funds were provided by 30 different firms. The primary source of input was annual fund factsheets provided by these firms, which by law have to disclose certain variables about the fund such as strategy, starting date, asset class, return, benchmark, fees, risk level, and turnover (FI 2004). TNAs for the funds were obtained from The Swedish Financial Supervisory Authority (Finansinspektionen, “FI”), whereas monthly fund net return series come from the SIX Trust database. These returns include reinvested dividends and are net of fees, as is customarily (see e.g. Feibel, 2003, pp 70-2)⁴. See Table A I in the appendix for a complete list of these primary variables obtained from external sources, and Table A II for secondary variables constructed out of the primary variables.

Out of information in the factsheets and taking into account index name changes, we reconstruct 309 unique benchmarks based on 215 indexes. The funds are then assigned a benchmark identification number linked to the returns of these benchmarks, which in turn are calculated from the combination of one or several indexes. Monthly index returns for these series are taken from Thomson Datastream when available, otherwise from SIX Trust. Customized indexes were replicated when possible; this concerns for instance the index MSCI World Excluding Sweden⁵.

Exclusions

Due to limited information, we are unable to find benchmarks for all of the funds in our sample. Since changes in strategy or investment objective imply subsequent benchmark adjustments, we filter the data from funds with this status, causing the exclusion of 16 observations with entries for benchmark change⁶. Furthermore, in order to lower the chance of benchmark changes initialized by external factors, we exclude funds whose index series cease to exist within two years (this affects 37 observations in total). These filters are applied to all tables and analyses.

Where the variable *Flow* is used (which includes all regressions) we apply additional filters. Firstly, we exclude funds with an age under two years prior to the arrival of flow to avoid potential extreme values due to start-up effects. It follows that in Model 3, since lagged flow is

⁴ More exactly they are adjusted for management fees and transaction fees, but not for front-end loads and deferred sales charges levied on investors.

⁵ We constructed this type of indexes by rebalancing the original index after setting the weight for Sweden equal to zero. We assumed the following original weights for Sweden: 0.87 percent for MSCI World, 0.88 for MSCI World Net, and 0.82 for MSCI World AC. These were the actual weights in 2001. (Wilson, 2002; and MSCI, 2001)

⁶ Information on strategy changes and mergers are obtained from fund factsheets and Fondmarknaden (2008a).

used as an explanatory variable, funds younger than three years are disqualified. Secondly, we remove funds that merged or were liquidated within one year for the same reason. These exclusions are similar to those conducted by Chevalier & Ellison (1997).

Limitations

Data is plagued by missing observations on several levels, most notably in the variables benchmark, TKA, and turnover. The main reason for this is that not all fund factsheets were identified. Data on TNAs were first recorded in 2000 by the Swedish Financial Supervisory Authority; to compensate for this we use TNAs reported in fund factsheets for 1999. Some funds have tailored indexes, for instance the firm Folksam which superimposes ethical constraints on some of their benchmark indexes in 2004. Others combine indexes but do not report the weights. As a consequence, these funds are excluded since their benchmark cannot be replicated without further information. Moreover, since benchmark information is available first in year 1999 the first year drops out of the sample as we look for benchmark changes from one year to the next.

Out of originally 492 funds, 444 remain after all exclusions. However, there are still considerable gaps in the data and only 168 of the funds have data entries in all years. To make use of as much data as possible, the sample sizes vary between tables and analyses. In Table II, Table A IV, and Table A VIII we exclude funds with missing observations as we look over the whole sample period. For the regressions, analyses, and tables in Section V we exclude funds that in a given year do not have observations for all variables used, thereby limiting the sample to 362 funds. Finally, in Section VI the number of observations drops further due to the fact that the explanatory variables are lagged. As a matter of consistency, we examined the findings in Section V and they are robust also to this smaller sample size.

Descriptive Statistics

Descriptive statistics for the main variables per asset class are presented in Table I. We see that funds investing in different types of securities (equities, fixed income, and both) differ somewhat in characteristics and separate analyses can therefore be of value. We also expect the distributions of equity and fixed income fund returns to differ; whereas monthly equity returns can be assumed to be normal, the same assumption for the returns on fixed income instruments is less feasible (see e.g. Smithson, 2003; and McGinty et al, 2004), and virtually all relevant previous studies analyze equity fund data only.

Table I
Descriptive Statistics

This table shows descriptive statistics for variables of the funds in our sample over the period 2000-2004. The funds are classed into three groups based on asset class, and for each group the mean and cross-sectional standard deviation of various characteristics are presented. "Mixed" refers to funds that invest in both equities and fixed income instruments. With ethical funds we refer to funds that employ any form of ethical screening. The last row refers to the percent of funds that belong to the banks SEB, Nordea, Swedbank, and Handelsbanken.

Fund Asset Class Statistic	Equity		Fixed Income		Mixed	
	<i>mean</i>	<i>st. dev.</i>	<i>mean</i>	<i>st. dev.</i>	<i>mean</i>	<i>st. dev.</i>
Fund Return (1 yr, %)	-3.6	12.6	4.5	2.2	-1.4	7.0
Benchmark Return (1 yr, %)	-2.2	10.3	5.1	2.3	0.7	5.6
Standard Deviation (%)	23	6.1	2.5	1.9	12	5.4
Flow (%)	24	60	26	146	36	120
Size (TNA, SEK bn)	1.4	2.6	2.3	4.9	3.0	5.5
Age (yrs)	8.3	5.1	10.3	4.8	7.7	4.2
Turnover	0.8	0.53	2.1	1.34	1.3	0.61
Fees (TKA, %)	1.8	0.67	0.6	0.27	1.3	0.54
Number of Observations	1139		298		122	
Number of Funds	320		86		38	
% ethical funds	14		5		9	
% of funds provided by main bank	50		57		39	

Figure 2 shows the five most common benchmarks in each year. We can see that in year 2000 twenty funds switch away from Affärsvärldens generalindex (AFGX), a broad market index incorporating all shares on the Stockholm Stock Exchange. 80 percent of these funds swap to SIX PX, which differs by the fact that it imposes a weight-restriction of 10 percent in any single stock; this is in line with the UCITS directive that imposes a similar restriction on mutual funds in the EU. According to Pettersson (2008a) at the Swedish Investment Fund Association, the reason why so many funds changed from AFGX to SIX PX is that there was a very large difference in index returns around this particular year (see Figure A 1). Likewise fund managers turned away from the hard-to-beat⁷ return index SIX RX, which in 80 percent of cases was substituted for SIX PRX. The increase in MSCI World is due to a move away from MSCI All Country World and FT World.

Basically all bond indexes in our sample are total return indexes, taking into account both interest payments and capital gains. The same is not true for equity indexes though; out of 197 identified benchmarks, only 25 are based on indexes that reinvest all dividends. As can also be seen in the same graph, over the whole period, only 16 percent of equity funds use benchmarks that include dividends. For ethical equity funds, the figure is slightly higher, at 26 percent, whereas at 8 percent it is substantially lower for funds belonging to the main four banks. Controlling for all of our control variables defined in Section II B4 as well as *Flow* and *ex_return_{old}*, the partial correlation coefficient between the use of benchmarks that include dividends and *MainBank* is negative and significant at a one percent level. The same is true for *TKA* (see Table A III).

⁷ As we saw in Figure A 1, in the period 1996-2004, SIX PX consistently underperformed AFGX and SIX PRX consistently underperformed SIX RX.

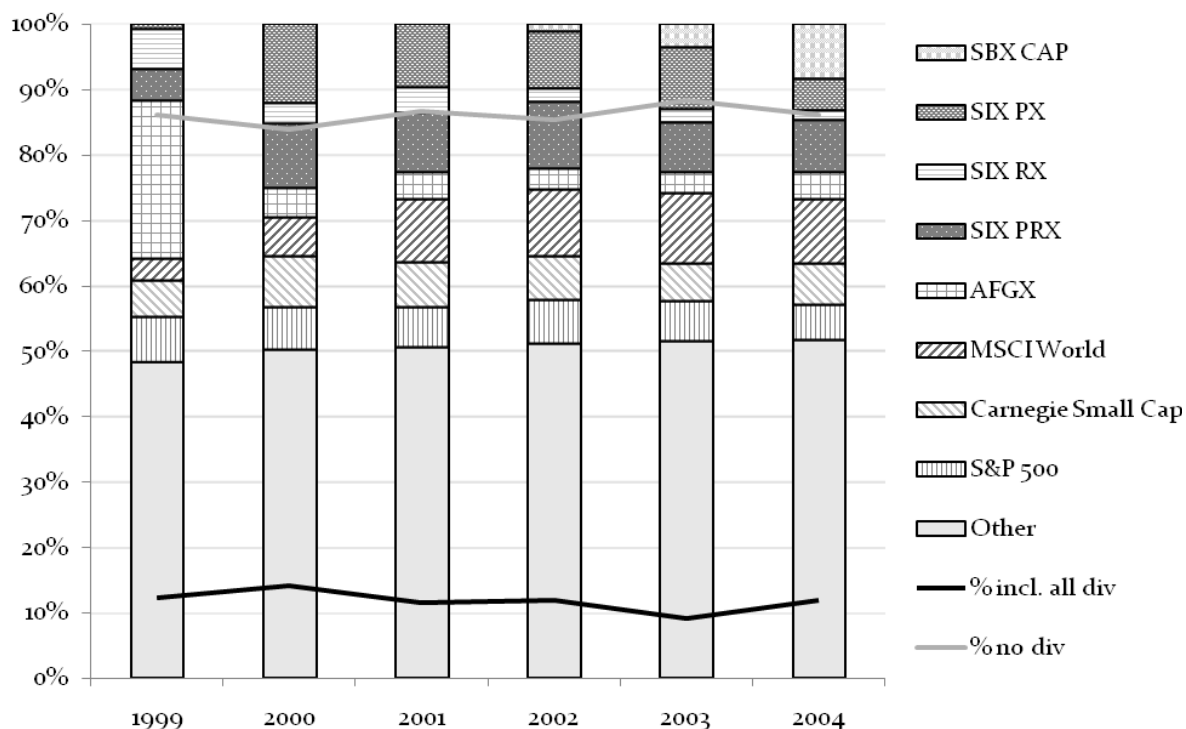


Figure 2. The 5 Most Common Equity Fund Benchmarks each Year

This graph shows the benchmarks for each year for the equity funds in our sample. SBX CAP, SIX PX, SIX RX, SIX PRX, and AFGX are different indexes tracking the overall development of the Stockholm Stock Exchange. AFGX is a price index that covers all stocks traded on the exchange. SIX PX adjusts the AFGX by superimposing a maximum-weight restriction of 10 percent for any single stock in the index and SIX RX adjusts it by including dividends, whereas SIX PRX adjusts it for both these two features. SBX CAP (current OMXSB) comprises 80 to 100 of the largest and most frequently traded stocks on the exchange and furthermore imposes the maximum-weight restriction of 10 percent described above. The Carnegie Small Cap Index comprises firms on the same exchange in the Small Cap segment. The MSCI World Index and the S&P 500 are common indexes of global and US stocks, respectively. The two horizontal lines represent the percentage of equity funds that use benchmarks that include all dividends and exclude all dividends, respectively.

On the whole, we can spot two interesting trends in the data. Fees decreased over the period for funds in all asset classes (see Table A IV in the appendix). With the exception of fixed income funds, the proportion of benchmark changers also decreased (Table A V). This pattern could perhaps be explained by the development of the stock market during the period; 2000 was the year of the great stock market crash (see Figure A 1). Nevertheless, the majority of funds changed benchmarks at least once (see Table II below). Again, there are considerable differences between asset classes. Clearly, fixed income funds change more rarely. This is likely related to the lower variety of fixed income benchmarks; there are 0.27 unique benchmarks per fund for fixed income, as opposed to 0.45 benchmarks per fund for equity.

Table II
Frequency of Benchmark Changes

This table shows the number of funds in our sample that change benchmarks any time over the whole period 2000-2004. No Change means that a fund does not change benchmarks over the whole period. The funds that change are differentiated by their frequency of change, measured as the number of years with benchmark changes. The funds are further classed into three groups based on asset class of investment. All funds with missing values for any year during 1999-2004 were excluded.

Fund Asset Class:	Equity	Fixed Income	Mixed	All
No Change	56	19	4	80
Change	63	7	8	88
<i>Change in</i>				
1 year	39	6	4	51
2 years	12	1	1	20
3 years	11	0	2	15
4 years	1	0	1	2

IV. Hypothesis 1 – *Direction of Change*

If the relative performance of funds vis-à-vis their benchmarks were irrelevant, then among funds that change benchmarks, there would be an even distribution in frequencies between changes to harder and changes to easier benchmarks. In addition, on average, the new and old benchmarks should have the same return. Hence, a first step in probing our theory is to compare the distributions of the new and the old benchmarks.

By investigating the data we can see that the means of the new benchmarks are lower for all asset classes (see Table III). This seems to correspond to lower volatility on average (see Table A VI). We employ a *t*-test to test whether the differences in returns are statistically significant. For equity funds, the null hypothesis of equal means can be rejected with 99 percent confidence in favor for the alternative hypothesis that the mean of the new benchmarks is lower than the mean for the old benchmarks. For the other classes, the null can be rejected only at the 10 percent level, but these tests are invalid due to violation of the normality assumption. To overcome this problem, we perform a non-parametric Wilcoxon signed-ranks test of the medians. For the whole sample, the null hypothesis is rejected at the 5 percent level, with equity alone just slightly above with a p-value of 0.053. When looking at directions of change we see that 127 funds changed to an easier benchmark and only 86 changed to a harder, which is significant on a 1 percent level with a binomial probability test. Fixed income funds stick out; apparently there were more positive changes, but so the group is quite small (19 observations). The results are presented in Table III.

As we saw before, Table IV shows that there are some considerable differences between years. Many changes occurred in 2000, after the stock market crash, and this year was also characterized by quite large changes to easier benchmarks, on average. Looking at frequencies instead, there were more changes to easier benchmarks on average in all years, although only in 2002 and 2003 are the frequencies significant. In any case, these results suggest the inclusion of year dummy variables in later regressions to capture time-specific effects.

Table III
Comparisons of Mean Returns and Frequencies

The first part of this table contains annual mean returns of new and old benchmarks belonging to funds investing in equities, fixed incomes instruments, and both (mixed). Funds that do not change benchmarks are excluded from this analysis. Two tests are conducted to test whether the differences in mean and median returns are less than zero as opposed to the null hypothesis that they are equal. A p-value lower than 0.05 means that the difference is significant on a 5 percent level. The second part shows the number of observations with benchmark changes, presented in two groups depending on if the change is to an easier (lower return) or harder (higher return) benchmark. P-values are presented from binomial tests of whether the number of changes to easier is larger than the number of changes to harder. These values can be interpreted as the probability of obtaining such a difference or larger if the numbers are random and equally probable. n_{easier} is the number of changes to easier and n_{harder} the number of changes to harder in the population.

Mean Returns (1yr, %)	Equity	Fixed Income	Mixed	All	Min	Max
New benchmark	-5.4	4.4	-4.3	-4.3	-49	40
Old benchmark	-4.5	6.1	-3.2	-3.3	-41	41
Tests if $bmdiff < 0$:						
<i>T-test</i> (p-value)	0.007	0.078	0.071	0.001		
<i>Wilcoxon</i> (p-value)	0.053	0.492	0.020	0.016		
Frequencies	Equity	Fixed Income	Mixed	All		
Change to easier	97	8	22	127		
Change to harder	65	11	10	86		
Test if $n_{easier} > n_{harder}$:						
<i>Binomial test</i> (p-value)	0.007	0.820	0.025	0.003		

Table IV
Benchmark Returns per Year

This table shows annual mean returns of new and old benchmarks as well as the difference between these two ($bmdiff$) for funds that change benchmarks; first for equity funds separately and then for all funds. In the seventh column "All" refers to all years. The table also shows frequencies, presented as percent of changers to easier (lower one year return) benchmarks out of all changers in both directions. For $bmdiff$, one-sided *t*-tests are conducted for each year with the null hypothesis of equal difference and the alternative hypothesis that the return of the new benchmark is lower. For change to easier, binomial tests are performed for each year with the null hypothesis of that the numbers are random versus the alternative that they are consistently higher than fifty percent. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Equity Funds						
Mean Returns (1yr, %)	2000	2001	2002	2003	2004	All
New benchmark	-9.8	-11.6	-35.4	21.0	12.1	-5.4
Old benchmark	-8.3	-11.7	-34.7	23.2	12.1	-4.5
$bmdiff$	-1.53 **	0.11	-0.74	-2.27 **	0.06	-0.89 ***
Frequencies (% of changers)						
Change to easier	60	50	72 **	74 **	50	60 ***
All Funds						
Mean Returns (1yr, %)	2000	2001	2002	2003	2004	All
New benchmark	-7.9	-7.9	-28.2	19.3	10.8	-4.3
Old benchmark	-6.7	-8.0	-26.6	21.1	12.0	-3.3
$bmdiff$	-1.25 **	0.12	-1.65 **	-1.82 **	-1.13 *	-0.99 ***
Frequencies (% of changers)						
Change to easier	60 *	50	72 **	69 **	57	60 ***

Robustness Checks

The finding of changes to easier benchmarks is robust. Even after adjusting for asset class and excluding special fund types such as hedge funds and funds that merged, died, or changed strategy over the period and in addition extending the performance measurement period to two and five years respectively, the same pattern persists: for funds that changed benchmarks, on average the performance of the new benchmark was consistently worse than that of the original benchmark. In Table A VII in the appendix the results are presented using Jensen's alpha as performance measure, from which the same conclusion can be drawn.

V. Hypothesis 2 – Influence of Performance

Now that we see that funds change to easier benchmarks on average, the question may be asked: what could cause these changes? Since a change of benchmarks by definition implies a change in a fund's excess return, one of the most probable factors to influence the direction of change is the excess return of the fund over its old benchmark, ex_return_{old} – that is, the fund's excess return prior to the change. Table V shows the distribution of this variable first for equity funds that do not change benchmarks and then for funds that change. For each year, tests of whether the means and medians of the variable are the same for the two groups are performed. In the second subsection of the table a similar comparison is done between changers to easier versus changers to harder. Clearly, for every single year, the changers to an easier benchmark have a lower excess return than the funds that change to a harder, and the difference is significant for all years except in 2004. A very interesting continuum emerges when comparing the three groups of non-changers and changers to easier and harder benchmarks: for every single year except 2004, the mean of the excess returns is lowest for the group of changers to easier benchmarks, followed by the group of non-changers, and finally the group of changers to harder benchmarks has the highest excess returns.

Table V
Excess Returns over Time for Different Groups of Equity Funds

This table shows the yearly excess return per year for equity funds in our sample. The excess return is defined as the difference between the return on a fund and its old benchmark. A fund's old benchmark is the benchmark reported in the previous year's factsheet for the fund. The funds are grouped based on benchmark change status. First the two groups of funds that change and not change are compared. Second, within the group of changers, excess returns for funds that change to easier and harder benchmark respectively are presented. The *t*- and Wilcoxon tests check whether the means and medians of the two groups are equal, respectively. A p-value lower than 0.05 suggests that the difference is significant on the 5 % level.

ex_return_{old} (%)	2000	2001	2002	2003	2004
Non-changers	1.2	-2.9	-3.1	0.5	-1.3
Changers	-1.2	-1.1	-3.9	-1.9	-4.0
<i>T</i> -test (p-value)	0.021	0.920	0.265	0.016	0.000
Wilcoxon (p-value)	0.172	0.961	0.062	0.001	0.000
Change to easier	-3.1	-3.6	-6.1	-3.4	-5.0
Change to harder	2.1	1.2	2.0	0.7	-3.5
<i>T</i> -test (p-value)	0.016	0.000	0.006	0.020	0.226
Wilcoxon (p-value)	0.010	0.001	0.001	0.045	0.330

For the whole sample of funds (equity, fixed income, and mixed), we perform Wilcoxon-Mann-Whitney tests to check whether the excess return of funds changing to an easier benchmark is lower than that of funds changing to a harder benchmark. In accordance with our theory, the null hypothesis of no difference can be rejected at a five percent level of significance for all years. It can also be rejected individually for the three asset class groups over the whole period. Overall, the probability of ex_return_{old} being lower for funds changing to an easier benchmark is estimated to 69 percent. By further comparing the change patterns between a) funds with a negative excess return over their old benchmark with b) funds having a positive ditto, the data tells us that for the first group, 60 percent of the changers choose an easier benchmark and 40 percent a harder, whereas for the second group the relationship is the reverse: 40 percent choose an easier benchmark and 60 percent a harder. The similarity of the numbers ought to be a coincidence. The fact that there are more changers to easier on average (see Table III) is a consequence of that the first group is substantially larger than the second.

In Table VI we compare the means of other characteristics between the groups of changers to easier, changers to harder, and non-changers. It appears as if the variables size and age are primarily associated with the frequency of change, since they are larger for both groups of changers as opposed to non-changers. Indeed, over the whole sample period, these two variables are significantly larger for funds that change benchmarks compared to funds that do no change (see Table A VIII in the appendix). The same is true for the standard deviation, but in the opposite direction; it is significantly lower for changers. Regarding the direction of change, funds that change to harder appears to have lower fees on average and are less often owned by the four main Swedish banks. Flow exhibits a rather surprising pattern; however, due to high volatility in this variable, this seems to be a random effect since unlike the other variables its distribution over the three groups changes considerably when the sample size is altered.

Overall, the general picture is that variables other than the excess return could influence the benchmark change decision, and consequently we include these variables as controls in our upcoming analyses. The remainder of this section is divided into two subsections. In the first subsection, we examine the causal relationship between funds' excess returns and their benchmark change decisions in more depth and make inferences. A multinomial logit model is developed in line with our theory of three distinct outcomes following the change decision, and hence covers the direction of change. In the second subsection, we focus on the magnitude of change for which we use a fixed effects model.

Table VI
Characteristics for Different Groups of Equity Funds

This table shows the means of various characteristics for equity funds 2000-2004, grouped by their benchmark change status. With change to easier it is meant change to a benchmark with a lower one year return than the original benchmark, and vice versa for change to harder. Funds are defined as ethical if they apply ethical screening. The last row refers to the percent of funds that belong to the banks SEB, Nordea, Swedbank, and Handelsbanken. Funds with a missing value for any of the variables in the first column are excluded.

	Change to easier	No change	Change to harder
Returns (1 yr, %):			
<i>Fund</i>	-6.3	-1.5	-7.0
<i>New benchmark</i>	-5.4	-0.5	-7.3
<i>Old benchmark</i>	-2.9	-0.5	-9.5
Flow (%)	23.3	17.4	8.4
Standard Dev. (%)	22.1	22.8	21.0
Size (TNA, SEK bn)	1.90	1.43	2.03
Age (yrs)	10.3	8.6	10.4
Turnover	0.74	0.77	0.72
Fees (TKA, %)	1.87	1.88	1.69
Number of Observations	81	649	41
Number of Funds	68	256	38
% ethical funds	14	16	24
% of funds provided by main bank	54	52	34

A. The Direction & Frequency of Change

In line with our theory of a one-step decision tree with three alternatives, we can group funds in any given year into three categories based on their benchmark change decision: funds that change to an easier benchmark, funds that change to a harder benchmark, and funds that do not change benchmarks. These three groups of funds are identified by the variable *bm_change* by being assigned the values -1, +1, and zero, respectively.

1. Regression Model

We form a multinomial logit regression model that aims to explain the direction of benchmark changes. A multinomial logit model is an extension of a general logit model that allows more than two discrete outcomes, and is useful for analyzing decisions. The multinomial logit model neither assumes a linear relationship between the dependent and independent variables nor that the relationship between these variables is the same for each categorical outcome. The only critical assumptions are that the categorical outcomes follow a log-normal distribution and that the outcome alternatives are independent of each other (independence of irrelevant alternatives, IIA).⁸

⁸ For more information about the logit model, see Gujarati (2003, ch. 15) and Greene (2007, ch. 23).

In our model, we set *bm_change* as the categorical and dependent variable. Our main independent variable is the fund excess return over its old benchmark, *ex_return_{old}*. In addition to this we include the control variables defined in Section II B4, which we see in Table VI have a tendency to vary across the three groups of changers. In addition, we include year dummy variables to control for unobservable time effects. Then by letting

P_0 : probability of not changing benchmarks

P_{-1} : probability of changing to an easier benchmark

P_1 : probability of changing to a harder benchmark

and making “not changing benchmarks” as the baseline category, we get the logit equation

$$\ln\left(\frac{P_j}{P_0}\right) = \beta_1 ex_return_{old_{i,t}} + \beta_2 Flow_{i,t} + \beta_3 StDev_{i,t} + \beta_4 Turnover_{i,t} + \beta_5 \ln TNA_{i,t} + \beta_6 \ln Age_{i,t} + \beta_7 TKA_{i,t} + \beta_8 Ethical_{i,t} + \beta_9 Mainbank_{i,t} + \gamma_t YearDummies_t + \varepsilon_{i,t} \quad (1)$$

where $j = \{1, -1\}$. We refer to this equation as Model 1. The coefficients, which are estimated through the maximum likelihood method, are in log-odds, meaning that the odds of changing to an easier or harder benchmark increases or decreases as a function of the independent variables.

2. Results

The regression results for model 1 are presented in Table VII. First estimates for equity funds separately are shown, then for all funds. The standard errors reported are White’s (1980) robust, generalized for within-cluster correlation⁹. These errors are found to be optimal for finance panel data sets (Petersen, 2006, and Thompson, 2006).

The excess return variable, *ex_return_{old}* is significant at the one percent level for all columns. The variable has a coefficient of -6.7 for changes to an easier benchmark and 10.4 for changes to a harder for equity funds. In other words, if the excess return increases by one unit, the log-odds of changing to an easier benchmark decreases by 6.7 and the log-odds of changing to a harder benchmark increases by 10.4. Figure 3 translates the numbers of these coefficients into probabilities. When the values of the control variables in the model are held constant at their averages, the lower the excess return, the higher the probability that the fund switches to an easier benchmark and the lower the probability that the fund changes to a harder benchmark, and vice versa. We also see that when the excess return is zero, the probability of changing to an easier benchmark is about eight percent, whereas the probability of changing to a harder benchmark is close to two percent. This can also be set in relation to the average excess return of -1.4 percent for equity funds. It is worth noting that the shape of the graphs is exponential: the probability of changing to a harder benchmark for instance is very low up to the point where the excess return turns positive, and takes off from there. This is just as we expect; managers of funds with a negative excess return have low incentives to switch to a harder benchmark as they are pressed not to present an unfavorable view vis-à-vis the benchmark to

⁹ See Rogers (1993) for more information on the generalization process and Wooldridge (2002, section 13.8.2) for a mathematical proof.

investors. If the fund is already outperforming its benchmark, however, this pressure should be less intensive. In the same way, we sense that this pressure causes the high propensity of underperforming funds to switch to an easier benchmark.

Table VII
Determinants of Benchmark Change Direction and Frequency

This table shows the estimated coefficients for Model 1 using cluster robust standard errors. The results were obtained by regressing a multinomial logit model with the categorical variable *bm_change* as dependent. The base-case is set as no benchmark change, and accordingly the coefficients tell the logg-odds of a change to an easier (lower one year return) or harder (higher one year return) benchmark depending on the explanatory variables in the first column. *ex_return_{old}* is a fund's one year excess return over its old benchmark. *Flow* is the yearly net flows to a fund. *lnTNA* and *lnAge* are the natural logarithms of TNA and fund age, respectively. *StDev* refers to a fund's standard deviation. *Ethical* is a dummy that takes the value 1 if a fund applies ethical screening. *MainBank* is a dummy that takes the value 1 if a fund belongs to one of the banks SEB, Nordea, Swedbank, or Handelsbanken. The values in parentheses are the absolute values of the z-statistics. The robust estimates are generalized for within-cluster correlation on the fund level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Type of Funds:	Equity				All			
Change Direction:	Easier		Harder		Easier		Harder	
<i>ex_return_{old}</i>	-6.708***	(4.03)	10.409***	(3.28)	-6.327***	(3.76)	8.283***	(2.87)
<i>Flow</i>	0.204	(1.57)	-1.485*	(1.84)	0.027	(0.55)	-0.424	(0.91)
<i>StDev</i>	-1.904	(0.96)	-2.112	(0.76)	0.467	(0.30)	-0.989	(0.49)
<i>Turnover</i>	-0.060	(0.18)	0.286	(0.89)	-0.394	(1.60)	-0.562**	(2.05)
<i>lnTNA</i>	-0.064	(0.58)	0.252*	(1.70)	-0.028	(0.32)	0.214*	(1.85)
<i>lnAge</i>	0.723**	(2.53)	0.956**	(2.44)	0.649***	(2.58)	0.818***	(2.59)
<i>TKA</i>	-15.449	(0.59)	-80.101**	(2.54)	10.109	(0.49)	-38.057	(1.48)
<i>Ethical</i>	0.685**	(2.06)	1.736***	(3.69)	0.717**	(2.19)	1.526***	(3.84)
<i>MainBank</i>	0.654**	(2.12)	-1.269***	(2.96)	0.464	(1.62)	-0.949**	(2.57)
<i>Year2000</i>	-0.507	(0.22)	-6.304**	(2.11)	-1.869	(1.03)	-6.123***	(2.70)
<i>Year2001</i>	-2.043	(0.89)	-6.991**	(2.34)	-3.077*	(1.66)	-6.224***	(2.72)
<i>Year2002</i>	-2.547	(1.13)	-9.038***	(3.05)	-3.710**	(2.12)	-8.160***	(3.44)
<i>Year2003</i>	-2.453	(1.11)	-9.265***	(3.09)	-3.832**	(2.16)	-8.552***	(3.53)
<i>Year2004</i>	-3.168	(1.42)	-9.448***	(3.24)	-4.206**	(2.32)	-9.105***	(3.95)
Observations	771		771		1025		1025	

We also find a weak relationship between flow and benchmark changes. The flow coefficient is significant for change to harder benchmarks at the ten percent level. The values of the log-odds coefficients, that are -1.5 for change to harder and 0.2 for change to easier, imply that an increase in flows, everything else equal, decreases the probability of changing to a harder benchmark, but increases the probability of changing to an easier one. Intuitively, we expect the opposite: funds with poor flow should be more willing to switch to an easier benchmark in order to increase their excess return and thereby attract more investment. On the other hand, this expectation is not straightforward given a potential reputation benefit of changing to a harder benchmark and the fact that trust may be more important for investors than excess returns. In addition, the convex flow-performance relationship suggests that funds with already high flow have more incremental flow to gain through an increase in the excess return (more on this in Section VI and VII).

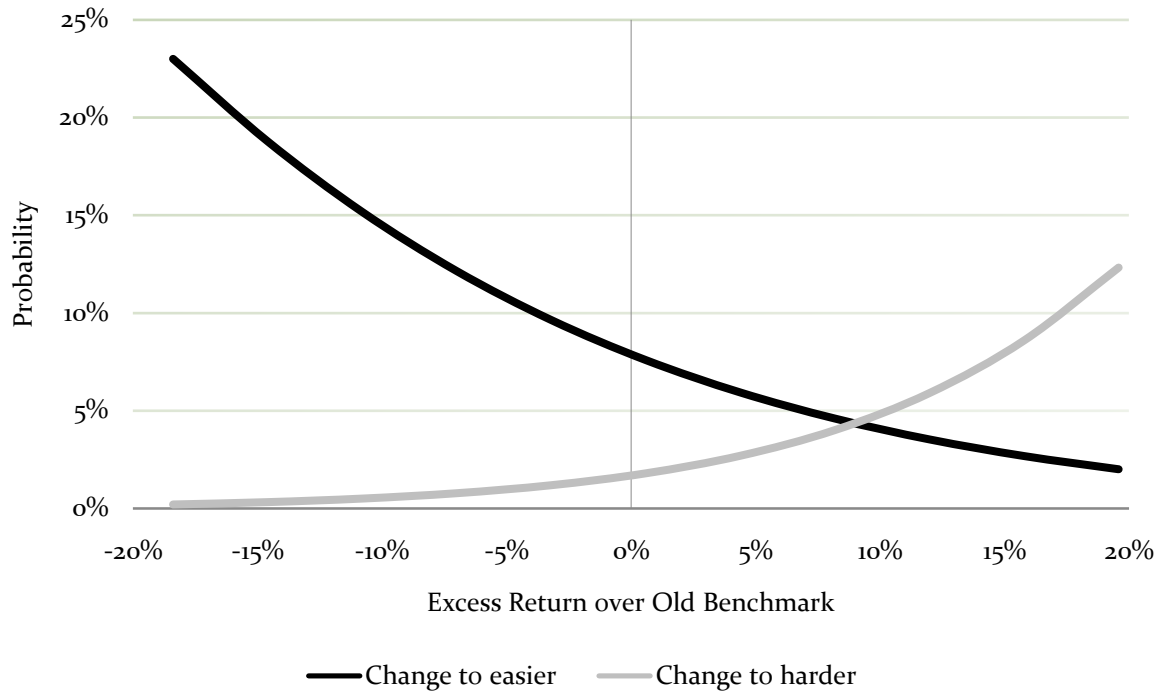


Figure 3. Probability of Change as a Function of Excess Return

This graph shows the probability of changing to an easier (lower one-year return) and harder (higher one-year return) benchmark, respectively, for equity funds, as a function of the excess return when the control variables in Model 1 are held constant at their means. The excess return is defined as the difference between a fund's annual return and the annual return of its old benchmark, where old benchmark is the benchmark the fund would have if it does not change benchmarks. The graph is based on the logit estimation results from regressing Model 1. The control variables are *Flow*, *StDev*, *Turnover*, *lnTNA*, *lnAge*, *TKA*, *Ethical*, *MainBank*, and *YearDummies*, as defined in the main text.

Several of the control variables have significant coefficients. Similar to the data investigation at the beginning of this section, the variable measuring age, *lnAge*, is associated with the frequency of change since the coefficients are of the same sign for change to easier as for change to harder. In other words, old funds are more inclined to change benchmarks in general, in both directions¹⁰. The same is true for funds that apply ethical screening, although being ethical is relatively more related to changes to harder than changes to easier benchmarks¹¹. For equity funds, the results are also similar for fees, measured by *TKA*, whose coefficients are negative and very large but only significant for change to harder benchmarks. This implies that funds with high fees have much lower propensity to change to harder benchmarks than do other funds, given everything else equal.

For equity funds, the dummy variable *MainBank* has a significant positive coefficient for change to easier (five percent level), and a significant negative coefficient for change to harder (one percent level). In other words, if a fund belongs to one of the four large banks in Sweden

¹⁰ Looking over the whole sample period, this effect is highly significant with a p-value of 0.000 (see Table A 5).

¹¹ When separating funds in two groups depending on whether a fund performs better than its old benchmark or not, we find that ethical funds are overrepresented in the group of funds that outperform their old benchmark in terms of one year return and subsequently change to a harder benchmark; 33 percent of these 40 funds are ethical, whereas for the five other groups (outperform and change to easier and not change, as well as underperform and change to easier, not change, and change to harder) the fractions of ethical funds are between 11 and 17 percent.

the odds of changing to an easier benchmark increases and the odds of changing to a harder benchmark decreases. This is interesting, especially in the light of the media coverage in recent months which has mostly centered on the practices of these banks (see Section I). The result is discussed more thoroughly in Section VII.

Lastly, the year dummies are all negative. Both the values and significances of the coefficients are more noticeable for changes to harder. This corresponds well the general trend of more changes to easier than harder benchmarks, as we saw in Section IV.

3. Robustness Checks

To check the robustness of our model, we first perform Hausman's specification test (see Hausman & McFadden, 1984) and the Small-Hsiao test of the IIA assumption (see Small & Hsiao, 1985). None of the tests can reject the hypothesis that the odds are independent of other alternatives, and hence there is evidence in favor for that this assumption of the logit model is not violated.¹² We then perform Likelihood Ratio and Wald tests to see if the categories can be collapsed. Both tests strongly rejects the null hypothesis that all variable coefficients associated with a given pair of outcomes are zero (all p-values are 0.000), implying that the categories cannot be combined. Finally, Likelihood Ratio and Wald tests of independent variables are conducted. Both tests reject the hypothesis that all coefficients associated with *ex_return_{old}*, *Flow*, *Ethical*, *lnAge*, *MainBank*, and *YearDummies*, respectively, are zero at five percent level of significance. The variables *Turnover*, *lnTNA*, and *StDev* on the other hand are not rejected, which is not surprising given their insignificant coefficient estimates shown in Table VII. The results from these tests suggest that Model 1 is appropriate.

In Table A IX Model 1 is re-estimated with *ex_return_{old}* replaced by *alpha_{old}*. In the first regression *bm_change* is used as categorical variable and in the second *bm_change_{alpha}*. This variable takes the value -1 if a change results in a lower alpha, 0 for no change, and 1 for a change to that gives the fund a higher alpha. All signs of the coefficients when *bm_change* is used are the same as in Table VII. When *bm_change_{alpha}* is employed they are of the opposite sign – just as we expect given the definition of the variables (see Section II B.2). Hence using alpha as performance measure does not alter our conclusions.

B. Determinants of the Magnitude of Change

The results from the logit model indicate that the level of excess return has a significant impact on the direction of benchmark change; a decrease in the excess return is associated with a higher tendency to change to an easier benchmark, and vice versa. In addition, certain properties such as ethical screening and fund age are positively related to the frequency of change in both directions, whereas other variables affect the probability of change positively in one direction but negatively in the other. However, although the multinomial logit model is powerful in identifying variables with a causal link to the discrete direction of change, it does not tell us anything about the magnitude of change – that is, how much easier or harder

¹² The Hausman test is clearly insignificant with values of the χ^2 distribution around 0.5 corresponding to p-values of 1.000. The Small-Hsiao test has values of χ^2 near 20 and p-values 0.101 and 0.123, for the two outcomes respectively.

benchmarks funds change to. In this section, we extend our analysis by developing a model that allows us to investigate how the relative performance of funds that change benchmarks affects this magnitude.

1. Regression Model

We use a linear regression model with the difference in one year return between the new and old benchmarks, $bmdiff$, as dependent variable. Clearly, if a fund changes to an easier benchmark this variable takes a negative value, and vice versa. Due to its property of continuity, $bmdiff$ allows us to measure both the direction and magnitude of change. As in the logit model, we use the fund excess return over its old benchmark, ex_return_{old} , as independent variable and in addition to this include various control variables. However, the variables *Ethical* and *lnAge* are found in the logit regression to be significantly associated with more changes in both directions. Additionally, they are found to be highly insignificant and increase the level of multicollinearity in Model 2 described below so these variables are left out. Observations with no benchmark changes are also excluded from this regression.

We use a fixed effects model to capture unobservable fund-specific characteristics that might affect funds' benchmark change decisions. These characteristics could be for instance policy, culture or manager personality. The model works by assigning a unique intercept to each fund through the inclusion of fund dummy variables. In this process, the *MainBank* dummy is dropped through absorption. The regression model is then as follows:

$$bmdiff_{i,t} = \alpha + \beta_1 ex_return_{old_{i,t}} + \beta_2 Flow_{i,t} + \beta_3 StDev_{i,t} + \beta_4 Turnover_{i,t} + \beta_5 lnTNA_{i,t} + \beta_6 TKA_{i,t} + \gamma_t YearDummies_t + \delta_i FundDummies_i + \varepsilon_{i,t} \quad (2)$$

2. Results

The results are presented in Table VIII using within-cluster robust standard errors as groupwise heteroscedasticity is detected. The second and third columns contain the coefficients for Model 2 for equity funds separately and for all funds, respectively.

For all estimation techniques used, the coefficient of the excess return variable turns out near a value of 0.3. This value is significant at the one percent level with robust standard errors. The value can be interpreted as if the fund excess return decreases by 1 percent, on average, funds that change benchmarks tend to choose a new benchmark that has a one year return that is 0.3 percentage points lower relative to what they would have chosen otherwise, keeping the other variables in the model constant. This is as we would expect; funds with a low excess return in a given year compared to other funds have a stronger incentive to choose a benchmark that has performed badly and thereby increase their after-change excess return, quantified by the variable ex_return_{new} .

Table VIII
Determinants of the Magnitude of Change

This table shows the estimated coefficients for Model 2 for equity and all funds, respectively (columns two and three). Additionally, it shows coefficients for Model 2 with the fund dummy variables replaced by fund manager dummies (column four). The results were obtained by regressing a fixed effects model with the variable *bmdiff* as dependent and the variables in the first column as independent. *bmdiff* is defined as the difference in one year returns between a fund's new and old benchmark. *ex_return_{old}* is the excess return of a fund over its old benchmark. *Flow* is the yearly net flows to a fund. *lnTNA* is the natural logarithm of TNA. *StDev* refers to a fund's standard deviation. *Ethical* is a dummy that takes the value 1 if a fund applies ethical screening. The constant is the average value of the fixed effects. The values in parentheses are the absolute values of the *t*-statistics using fund cluster robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Type of Funds:	Equity		All		Equity	
Fixed Effect:	Fund-specific		Fund-specific		Manager-specific	
<i>ex_return_{old}</i>	0.316***	(2.91)	0.316***	(2.78)	0.222***	(2.82)
<i>Flow</i>	-0.007	(1.07)	-0.008	(1.14)	-0.003	(0.62)
<i>StDev</i>	-0.833*	(1.80)	-0.819**	(1.98)	-0.685**	(2.27)
<i>Turnover</i>	-0.039	(0.94)	-0.027	(0.93)	0.010	(0.64)
<i>lnTNA</i>	0.026	(0.46)	0.010	(0.18)	0.004	(1.51)
<i>TKA</i>	13.472**	(2.09)	10.834**	(2.07)	-2.479**	(2.39)
<i>Year2001</i>	0.049*	(1.85)	0.047*	(1.81)	0.045***	(2.71)
<i>Year2002</i>	0.136*	(1.76)	0.119*	(1.67)	0.114***	(2.81)
<i>Year2003</i>	-0.017	(0.26)	0.006	(0.12)	-0.006	(0.17)
<i>Year2004</i>	-0.026	(0.57)	-0.036	(0.92)	-0.051**	(2.22)
<i>Constant</i>	-0.598	(0.50)	-0.222	(0.20)	0.088	(1.09)
<i>Observations</i>	122		150		121	
<i>R</i> ²	0.89		0.89		0.71	
<i>Adj. R</i> ²	0.88		0.89		0.68	

Looking at the control variables, *TKA* is significant at five percent and the fund risk level, *StDev*, at ten percent. Surprisingly, and in contrast to the logit model, the sign of the *TKA* coefficient is positive. Its considerable size implies that given that a fund will change its benchmark, if total fund fees increases by one percentage unit and the other variables stay constant, it will on average change to a benchmark with a return that is 13.5 percentage points higher than the benchmark it would otherwise have changed to. As for the risk level, if the fund standard deviation increases by one percentage unit, the fund will on average change to a benchmark with a return 0.83 percentage points lower than otherwise. In the logit model however, although mainly insignificant, these two variables have the same sign of the coefficients in both outcomes, indicating that they affect the propensity rather than the direction of change; as a consequence we are hesitant to draw any conclusions.

3. Robustness Checks

We regress Model 2 using a fixed effects estimator as it is the most theoretically and statistically appealing approach. To check for model misspecification, we use the test developed by Chow (1960). With a value of the *F*-statistic of 1.77 the null hypothesis of pooled OLS is rejected. A highly insignificant Hausman test also rules in favor for a fixed effects model as opposed to a random effects model, with a χ^2 of 8.18.

For our main setting of the model, fund-specific fixed effects are used. One could also imagine the unobservable effects to be on a fund manager or firm level (like in Sensoy, 2008)

since personality is linked to the fund manager and culture and policies can be the same within a firm. In the last column in Table VIII estimates are presented for the case of manager-specific effects. Nevertheless, the adjusted R^2 is lower and Akaike (AIC) and Bayesian (BIC) information criteria higher for these two alternatives as opposed to our initial model, indicating that they have lower explanatory power¹³.

To test the robustness of our model with respect to the choice of performance measure we rerun our regression with ex_return_{old} replaced by $alpha_{old}$ and $bmdiff$ replaced by $alphadiff$ (Table A IX). The signs of the coefficients are the same as in Table VIII for the columns where $bmdiff$ is used and opposite in the columns using $alphadiff$ as dependent variable. This suggests that our results are robust to the use of Jensen's alpha as performance measure.

We utilize Wooldridge's (2002) test for autocorrelation in panel-data models as validated by Drukker (2003), which with an F -statistic of 2.02 fails to reject the null hypothesis of no first-order autocorrelation at any reasonable levels of significance. However, groupwise heteroskedasticity is detected with the modified Wald test for fixed effects models. To overcome this problem we report all our estimates using the White (1980) robust standard errors generalized for clustering. Multicollinearity does not seem to be a serious problem in our model (see Table A XI and Table A XII). All variables except size ($lnTNA$), fund risk ($StDev$), and TKA have levels of the variation inflation factor (VIF) lower than 3. Overall, there are no simple Pearson correlation coefficients larger than ± 0.5 . Partial correlation coefficients lie around 0.5 between $lnTNA$ and $StDev$ whereas it is less than ± 0.15 between all other explanatory variables. Skewness and kurtosis tests of the residuals suggest that they are not normally distributed; however this problem is mitigated through the Central Limit Theorem.

VI. Hypothesis 3 – Impact on Flow

Our last hypothesis relates the findings from the previous hypotheses to the behavior of investors. Given that funds change to easier benchmarks on average, and that this practice is more prevalent among funds that underperform their original benchmark, what is the reaction of investors? The most common and statistically satisfying way to investigate investment behavior on the aggregate level in the fund management industry is to look at flows into and out of funds. To see whether benchmark changes have an effect on investors' choice it is therefore natural to examine determinants of flow. To do this, we follow the procedure of other authors in the academic field by building new structures upon the existing framework.

It is widely known that past performance is one of the most important factors that investors evaluate before investing in a fund, and many studies have looked at the relationship between performance and flow. The literature using US mutual fund data, ranging from 1965 up till today, finds a consistent J-shaped positive relationship between flows and performance. This relationship is characterized by on the one hand poorly performing funds with a consistent lousy track record due to their high fees, and recently high performers, who attract the lion's

¹³ The AIC and BIC for Model 2 with fund-specific effects have the values -665 and -637, respectively, whereas the AIC and BIC for the same model using manager-specific effects are -534 and -503, respectively. The AIC is calculated as in Akaike (1973) and BIC as in Schwarz (1978).

share of investment but whose performance proves to be temporary in the long run (Patel, Zeckhauser, and Hendricks, 1994; Hendricks, Patel, and Zeckhauser, 1993; Ippolito, 1992; Grinblatt & Titman, 1992; Goetzmann & Ibbotson, 1994; Gruber, 1996; Carhart, 1997; Hendricks, Patel, and Zeckhauser, 1997; Brown, Goetzman, Ibbotson, and Ross, 1997; Chevalier & Ellison, 1997; Sirri & Tufano, 1998; Del Guercio & Tkac, 2001; Goetzmann & Massa, 2003; Lynch & Musto, 2003; and Bollen & Busse, 2004). In contrast to this, Del Guercio & Tkac (2002) find a linear relationship in the US pension fund market: investors withdraw assets from poorly performing funds and do not disproportionately flock to recent outperformers. This is explained by a more sophisticated investment behavior, reflected by the difference in selection criteria and evaluation procedures between investors in the two markets. Ruenzi (2005) reaches a similar conclusion when examining different segments of the mutual fund industry: specialist segments exhibit a more linear relationship whereas for standard segments it is more convex.¹⁴ By comparison, for the Swedish market, which has a large proportion of private small-scale investors, one would then expect a J-shaped graph; however, to our knowledge, no study has been undertaken to validate this belief. A paper by Dahlquist, Engström, & Söderlind (2000) fails to find evidence for a relationship between past performance and flow among Swedish funds. Indeed, since it has been shown that performance persistency is limited to periods up to one year, several authors question the rationality of investors in chasing past winners altogether (see e.g. Berk & Green, 2004); yet on the other hand, to our knowledge there is no better indicator of manager skill, and hence there is reason to believe that performance in relation to a passive benchmark still does matter a great deal to Swedish investors. A recent customer survey for instance finds that past performance is the single most important criterion for investors when evaluating a mutual fund (The Swedish Investment Fund Association, 2006). Accordingly, we expect an effect on flow from benchmark changes since these alter a fund's excess returns.

In the following part of this section, we develop a model that attempts to explain flow through fund performance and benchmark changes while controlling for other factors. This will provide us with insights on whether benchmark alterations have blessed funds with more or less flow; that is, if this practice has any effect on investors' investment decisions.

1. *Regression Model*

We follow the latest academic procedure and develop a regression model that allows for a piecewise linear relationship between flow and performance¹⁵. The dependent variable of the model is *Flow*, which as defined in the Section II B.3 is calculated as the yearly growth in fund TNA not attributed to the return or dividends on the funds' securities. As explanatory variables, we include three performance ranking variables that together provide the different slopes needed to build the J-shaped relationship. To form these variables, we rank each fund according to its performance relative to other funds. The rankings are then evenly redistributed between zero and one and recorded in the variable *Rank*. Finally, the three

¹⁴ The conclusion of these authors is similar to Gruber's (1996) explanation through the existence of a "disadvantaged clientele" which holds on to poor performers due to either a) asymmetric information, b) taxes, or c) investment restrictions. One investment restriction could be that of short-selling (Lynch & Musto, 2003).

¹⁵ See Gujarati (2003, pp 317-320) for general information about piecewise regression models.

performance ranking variables are generated by separating the bottom, three middle, and top quintiles of fund rankings. We follow this technique, originally developed by Sirri & Tufano (1998), as it has been shown that basing performance on rankings in this way explains flows better than standard cardinal measures (Patel, Zeckhauser, and Hendricks, 1994; and Navone, 2002).

The most influential papers have used various measures of performance, such as raw returns or returns in excess of a market index (e.g. Chevalier & Ellison, 1997; Patel, Zeckhauser, and Hendricks, 1994; Sirri & Tufano, 1998; and Jain & Wu, 2000), Jensen's alpha or multifactor alphas (Patel, Zeckhauser, and Hendricks, 1994; Gruber, 1996; Jain & Wu, 2000; Lynch & Musto, 2003; Del Guercio & Tkac, 2002; and Kempf & Ruenzi, 2008) as well as Sharpe ratios (Patel, Zeckhauser, and Hendricks, 1994; and Kempf & Ruenzi, 2008). Since the additional factors needed to calculate the Fama-French (1993) three-factor and Carhart (1997) and Gruber (1996) four-factor alphas are unavailable for the Swedish market, we use the one-factor alpha as developed by Jensen (1968) as risk-adjusted performance measure (α_{old}). In addition to the alpha, we also estimate our model using the excess return, ex_return_{old} , as performance measure. We use the old benchmark when calculating these performance measures since we want the ranking variable to capture the effect on flow from fund performance irrespective of benchmark changes.

With the general effect of performance having been isolated through the ranking variables, we may look specifically at the impact of benchmark changes on flow. To do this, we develop four models that include various variables. In our first model, which we call Model 3a, we include the dummy *Change* that takes the value 1 if a fund changes benchmark and 0 if it does not. In our second model, Model 3b, we include the variables *ChngEasier* and *ChngHarder* that work in the same way but separate the effect of changing to easier and harder, respectively. In Model 3c and 3d we utilize the continuous variables *bmdiff* and *alphadiff*, and allow them to have three different coefficients depending on the performance ranking group a fund is in.

In addition to these main variables, a variety of controls are included. Most of these variables are defined earlier in this paper, but there are a few new to this model. Marketing is an important issue when it comes to mutual fund investments. Korkeamäki, Puttonen, and Smythe (2007) find that highlighting and informing investors about a performance achievement through advertisement is a requirement for fund flows to increase, and further effects of advertising and media coverage on flow are found by Gruber (1996), Sirri & Tufano (1998), Zheng (1999), Jain & Wu (2000), Barber, Odean, and Zheng (2005), Gualtieri & Petrella (2005), Cronqvist (2006), Gallaher, Kaniel, and Starks (2006), and Kaniel, Starks, and Vasudevan (2007). Even individual funds with little marketing expenses benefit in terms of flow from fund family marketing activity as all funds in the family (that is, belonging to the same company) are made more visible to investors (Huij & Verbeek, 2007). Since no public information on marketing expenses is available for our sample funds, we control for family-specific marketing efforts like Kempf & Ruenzi (2008) through the variable *FamilyFlow*. This variable is calculated as the sum of money flows to all funds in a fund family divided with the previous year's aggregated TNA for that family. Marketing isolated to a particular fund is then captured by the previous year's flow, which enters the model through the variable *Flow* lagged. This variable also covers a potential status quo bias among investors. Relating to this, the *Star* and *Dog* variables are dummies that take the value one if the family has a fund with a

performance ranking in the top 5th percentile or the bottom 5th percentile, respectively. These variables were introduced by Nanda, Wang, and Zheng (2004) to account for what they call the star phenomenon. Since it contains missing values, we exclude *Turnover* in order to gain more observations.

All the explanatory variables in the model are lagged one year. The reason for this is that the model assumes that investors base their investment decisions on information available at time $t-1$ and flows arrive subsequently between $t-1$ and t , thereby being accumulated in the variable *Flow* at time t . Following this adjustment, the regression model is

$$\begin{aligned} Flow_{i,t} = & \alpha + \beta_1 LowRank_{i,t-1} + \beta_2 MidRank_{i,t-1} + \beta_3 TopRank_{i,t-1} \\ & + \beta_4 ChangeDummies_{i,t-1} + \beta_5 Flow_{i,t-1} + \beta_6 FlowFamily_{i,t-1} \\ & + \beta_7 Turnover_{i,t-1} + \beta_8 lnTNA_{i,t-1} + \beta_9 lnAge_{i,t-1} + \beta_{10} Star_{i,t-1} \\ & + \beta_{11} Dog_{i,t-1} + \beta_{12} Ethical_{i,t-1} + \beta_{13} TKA_{i,t-1} + \gamma_t YearDummies_t \\ & + \delta_i FundDummies_i + \varepsilon_{i,t} \end{aligned} \quad (3)$$

where

$$\begin{aligned} LowRank_{i,t-1} &= \min\{Rank_{i,t-1}, 0.2\} \\ MidRank_{i,t-1} &= \min\{Rank_{i,t-1} - LowRank_{i,t-1}, 0.6\} \\ TopRank_{i,t-1} &= Rank_{i,t-1} - (LowRank_{i,t-1} + MidRank_{i,t-1}) \end{aligned}$$

Unlike the standard method used in similar empirical studies, which originates from Fama & MacBeth (1973), we estimate Model 3 using a fixed effects model with within-cluster robust standard errors (again, the *MainBank* variable is excluded for this reason). This estimation method is recommended e.g. by Petersen (2006) on ground that the Fama-MacBeth method is statistically naïve. We further exclude all fixed income and mixed funds, for three reasons. Firstly, we suspect that the flow-performance differs between equity and fixed income funds, which would make the estimates less efficient. Secondly, the vast majority of previous research has been undertaken on equity funds only and consequently the method used here might be inappropriate for other funds. Thirdly, because our dataset contains few fixed income and mixed funds, it is not possible to estimate separate coefficients for these groups.

2. Results

The main regression estimates are reported in Table IX using cluster robust standard errors and different measures of performance and benchmark change. The within- R^2 for the different models lie around 15 percent and is similar to that reported by other authors (by comparison, e.g. Kempf & Ruenzi, 2008, report an R^2 of 15 percent and Jain & Wu, 2000, an R^2 between 13 and 21 percent), but despite this most coefficients are not significant on the five percent level. Unlike the findings of the previous study on Swedish data by Dahlquist, Engström, and Söderlind (2000), the coefficient values of the three performance variables, *LowRank*, *MidRank*, and *TopRank*, all correspond to a J-shaped flow-performance relationship as we are to expect from the vast majority of previous empirical findings; however, they are not significant even on a ten percent level. The values of the coefficients for the ranking variables are similar to those obtained by Sirri & Tufano (1998) and can be interpreted as follows: for example, if a fund in the top rank manages to increase its ranking by ten percentiles (e.g. from the 85th to 95th percentile), keeping the other variables in the model constant, it receives between 12 and 15 percent more flow, depending on the ranking variable.

Table IX
Determinants of Flow

This table shows the estimated coefficients for Model 3 for equity funds. The results were obtained by regressing a fund and time fixed effects model with the variable *Flow* as dependent and the variables in the first column as independent. *Flow* is calculated as $(TNA_t - TNA_{t-1}(1+r_t))/TNA_{t-1}$ where TNA_{t-1} is a fund's total net assets at the previous year end $t-1$ and r_t is the yearly return of that fund. The three rank variables are performance measures based on excess returns and Jensen's alphas, respectively, both calculated yearly from monthly net returns in relation to the funds' old benchmarks. In Model 3a the dummy variable *Change* measures benchmark changes and takes the value 1 if a fund changes benchmark. In Model 3b this effect is captured by two dummies that take the value 1 if a fund changes to an easier and harder benchmark, respectively. For Model 3c, the variable *bmdiff* is multiplied by dummies depending on in which rank the fund is placed, allowing the coefficient of *bmdiff* to take different values for the three ranks. *bmdiff* is defined as the difference in one year returns between a fund's new and old benchmark. *alphadiff* is calculated by subtracting Jensen's alpha of a fund based on its new benchmark with the corresponding alpha obtained from regressing the fund's monthly returns (during a one year period) on its old benchmark. Subsequently, *alphadiff* is multiplied by dummies to allow different coefficients depending on the fund ranking (Model 3d). *lnTNA* and *lnAge* are the natural logarithms of fund TNA and age, respectively. *Ethical* is a dummy that takes the value 1 if a fund applies ethical screening. All explanatory variables except the time dummies are lagged one year. The values in parentheses are the absolute values of the *t*-statistics using fund cluster robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Model	3a		3b		3c		3d
Ranking Variable	<i>ex_return_{old}</i>	<i>alpha_{old}</i>	<i>ex_return_{old}</i>	<i>alpha_{old}</i>	<i>ex_return_{old}</i>	<i>alpha_{old}</i>	<i>alpha_{old}</i>
<i>LowRank_{t-1}</i>	-0.359	0.050	-0.457	-0.274	-0.269	-0.431	-0.324
<i>MidRank_{t-1}</i>	0.098	-0.061	0.079	-0.051	0.097	-0.002	-0.015
<i>TopRank_{t-1}</i>	1.153	1.523	1.183	1.344	1.010	1.541	1.469
<i>Change_{t-1}</i>	0.174*	0.183*					
<i>ChngEasier_{t-1}</i>			0.130*	0.126*			
<i>ChngHarder_{t-1}</i>			0.270*	0.282*			
<i>bmdiff_LowRank_{t-1}</i>					-0.231	-0.307	
<i>bmdiff_MidRank_{t-1}</i>					-0.645	0.839	
<i>bmdiff_TopRank_{t-1}</i>					7.421	0.926	
<i>alphadiff_LowRank_{t-1}</i>							4.515
<i>alphadiff_MidRank_{t-1}</i>							-6.192
<i>alphadiff_TopRank_{t-1}</i>							-14.560
<i>Flow_{t-1}</i>	-0.122	-0.116	-0.122	-0.116	-0.123	-0.115	-0.115
<i>lnTNA_{t-1}</i>	-0.183*	-0.183*	-0.184*	-0.185*	-0.172*	-0.178*	-0.177*
<i>TKA_{t-1}</i>	2.136	2.830	3.409	3.956	2.431	1.529	1.288
<i>Ethical_{t-1}</i>	0.272***	0.263***	0.293***	0.291***	0.274***	0.270***	0.256***
<i>lnAge_{t-1}</i>	-0.305	-0.321	-0.330	-0.348	-0.318	-0.298	-0.292
...							
Observations	595	595	591	591	591	591	591
R ²	0.63	0.62	0.63	0.63	0.63	0.62	0.62
Adj. R ²	0.62	0.61	0.62	0.62	0.62	0.60	0.60

Continuing to the benchmark change variables, the benchmark change dummy is significant on a ten percent level with a value of roughly 0.2. This means that on average, everything else equal, funds that change benchmarks receive the substantial amount of twenty percentage points more flow in the subsequent year; this can be seen in relation to the average flow for equity funds of 24 percent (see Table I). However, when examining the relationship more closely by controlling for the direction of change, we see in Model 3b that the largest increase in flows is actually attributed to changers to harder benchmarks – on average changers to harder increase their flows by about thirty percentage units whereas changers to easier increase their flow by about ten. This is not as we expect, since changers to harder lower their excess return. To investigate this phenomenon, we run further regressions. According to Model 3c and 3d, the rank of the fund seems to matter: increased flow follows from previous changes to an easier benchmark for the funds ranked in the bottom four quintiles based on the *ex_return_{old}* variable, whereas it follows from changes to harder for funds in the top quintile (Model 3c). Using the change in alpha measured by *alphadiff* (Model 3d) the coefficients are of the opposite sign as those obtained by *bmdiff*; just as we expect following the definition of the variable (see Section II B2). Although insignificant, the values can be interpreted like e.g. for funds in *MidRank*, on average and everything else equal, a change to a benchmark with a one-year return one percentage point lower than otherwise causes an increase in net flows the subsequent year by 0.65 percentage points. Overall, the different outcomes support the view that changes to a harder benchmark generates more flow than changes to an easier, but this depends on the fund ranking and is driven by funds in the top quintiles. This could be due to that funds in top rankings serve a more sophisticated clientele than other funds do. For this clientele, a change to a harder benchmark may be a signal of superior quality or manager skill. Since these funds already perform well, the pressure to present a better relative performance to investors ought to be less intensive and instead the reputation concern of relatively larger importance.

Among the control variables size, *lnTNA*, is significant on the ten percent level and *Ethical* on one percent. Several authors have argued that fund size should affect flow positively (see for example Gruber, 1996; Sirri & Tufano, 1998; and Del Guercio & Tkac, 2001 & 2002), due to economies of scale and the fact that size attracts more media attention. On other hand, our result for size is consistent with the common view on the market that an increase in size lowers the capability of managers to generate positive alpha or returns in excess of their benchmark; evidence for this view is found e.g. by Chen, Hong, Huang, and Kubik (2004). It can also be a consequence of the fact that flows are measured in percentage terms, which implies that for an equal amount of real money flows, the variable *Flow* will have higher values for smaller funds than for other funds. The coefficient for the variable *Ethical* is positive with a value near 0.3, meaning that ethical funds on average receive roughly thirty percentage points more flow than other funds. Given the large number this is a major finding yet not surprising considering the perceived popularity of ethical funds in Sweden.

The value of *TKA* is insignificant but positive. This is surprising but similar to the finding of Barber, Odean, and Zheng (2005) who obtain a positive coefficient of operating expenses due to the embedment of marketing costs. As opposed to Model 2, none of the year dummy variables are significant.

3. Robustness checks

Although alphas and excess returns are the most commonly used performance measures in the literature, as robustness check we regress model 3 using the Sharpe ratio. This results in different values and in some cases even different signs of the coefficients of *TKA*, *lnAge*, *StDev*, as well as *LowRank* and *TopRank*. Using a common market index (OMXS PI for Swedish equity funds and MSCI World Index for global funds) in the calculation of alpha (as opposed to fund-specific benchmarks) provides equally unsatisfactory results. This could be due to fund and index mismatches that may arise since unlike other authors we are unable to group funds per investment style. In order to check for the impact of extreme observations, we winsorize flows larger than 500 percent by setting them equal to the highest observation below the cutoff point. This affects in total 23 funds but not the estimation results. Neither does calculating flows in currency values (as opposed to in percentage of TNA), as in the classic article by Patel, Zeckhauser, and Hendricks (1994), alter the results much. Another variable of concern is the dropped *Turnover*; again, this exclusion has only a minor effect on the coefficients. Results from these regressions are available upon request.

As previously, we test our model for panel heteroscedasticity. A highly significant modified Wald test for groupwise heteroscedasticity justifies our use of within-cluster robust estimates (the p-value is 0.000). The Wooldridge test for autocorrelation in panel data yields an *F*-statistic of 1.21 which is not sufficient to reject the null hypothesis of no first-order autocorrelation.

Like in our previous model, the restricted *F*-test rejects the null of pooled OLS at the five percent level in favor of the fixed effects model, with an *F*-statistic of 1.85. Furthermore, the Hausman test tells us that fixed effects is clearly to be preferred to random effects, with a χ^2 -value of 822.

According to Pettersson (2008b), to avoid double taxation, most equity funds registered in Sweden pay out dividends equal to their net income which by law is set to a lump sum of 1.5 percent of TNA in any given year.¹⁶ These dividends are automatically reinvested into new shares of the fund, after a 30 percent tax deduction the investor level. To test for this market-specific effect, we subtract flows by the amount of the taxes; however no particular differences in our results are observed.

¹⁶ For more information, see the Swedish Investment Fund Association (2007), Gunne (2006), and Carlsson (2006). However, the practice varies among firms; some funds pay no dividends and others do not pay dividend each year (Fondmarknaden, 2008b).

VII. Discussion

We found evidence that the excess returns matter for funds that change benchmarks: if a fund underperforms its benchmark the probability is larger that it will change to an easier benchmark than to a harder one. However, it is not straightforward that underperforming funds should change to easier benchmarks. In fact, following from the J-shaped performance-flow relationship, it can be argued that the pressure to change to an easier benchmark is larger for top achievers, since they gain relatively more flow from an incremental improvement in performance. Yet this approach assumes that an increase in flow is equally valued regardless of the original level of flow. It also implicitly assumes that investors are homogenous, whereas in reality, as suggested in the classic paper by Gruber (1996), top achievers may attract a larger share of sophisticated investors and poor performers may be held by a disadvantaged clientele. This disadvantaged clientele reacts slower to performance in the sense that it does not swap funds rapidly, but is on the other hand more likely to respond positively to superficial adjustments in relative performance following benchmark changes. By contrast, star funds, whose main customers may consist of informed investors, have more to risk by changing to dubious benchmarks. We can conclude from this that the relationship between benchmark change and flow is rather complex. Nevertheless, given the propensity of funds to change benchmarks, in particular to easier ones, there should be some kind of relation to flow – unless the activity is driven by other reasons, such as prestige.

Actually, there is some evidence in opposition to the assumption of Chevalier & Ellison (1997) that funds' unspoken main objective is to maximize flows. For example, there are plenty of funds that actually restrict the inflow of capital in order to avoid the side-effect of distorted alpha or excess return. Although this could just as well be a marketing trick, one cannot deny that at least some funds have maximizing returns per se as their main objective. Yet the main underpinning of our theory, that benchmark changes are influenced by relative performance, is not violated by the fact that maximizing flow may not constitute the main incentive for improving relative performance. Indeed, as already hinted at in Section II, manager-specific and other causes can lie behind this motive. As Chevalier & Ellison (1999a) show, career concerns of managers influence investment decisions taken by the fund, fund performance, as well as managers' level of risk-taking. It is equally reasonable that these concerns may influence benchmark changes. On the manager level, the tradeoff between appropriateness and looking good translates to a function of utility maximization dependent on trustworthiness (having a representative benchmark) and prestige (outperforming this benchmark). The prestige aspect does not have to be related to performance-pay schemes – which by the way are relatively rare in Sweden (in our sample, only eleven funds reportedly use them), compared to their by Basak, Pavlova, and Shapiro (2007) documented prevalence in the USA; there are other positive career effects that are likely to accrue to fund managers that outperform their benchmarks in the long run, plus potential non-career effects.

We obtained positive coefficients for the dummy variables on benchmark change in the flow regression. The values are surprisingly high in relation to the performance ranking coefficients. This is somewhat puzzling since we expect all additional flow following a benchmark change to be attributed to the change in relative performance, measured either by excess returns or alpha. Even more puzzling is that more flow is expected from changes to a harder benchmark

than changes to an easier one. The most likely explanation is that these variables capture more effects than just that following from benchmark-caused changes in relative performance. What these other effects may be we do not have an answer for, but leave up to future research to find out.

Overall, regardless of direction, we expected flows to be positively related to benchmark changes. This however is not an obvious expectation. Based on our own experience in the industry and conversations with fund managers, trust is perhaps the most important factor for investors when deciding whether to invest in a fund or not, and could be the main reason why investors still prefer actively managed funds to passive index-trackers. Accordingly, one may argue in the opposite way as our third hypothesis, namely that investors should penalize funds that change benchmarks too much, as a consequence of disapproving reliability. In that case, these funds should receive *less* flow. Indeed, the concern of trust may serve as a self-regulatory force on the firms in the mutual fund industry regarding the issue of benchmark changes. Yet it was only recently (in January 2008) that the discussion of inappropriate benchmarks was brought to light in Sweden, so we think that the overall effect from changes to easier benchmarks should be positive on the average investor. We use the notation average investor here, because it is clear that not all investors look at a fund's excess returns. In fact, the definition of excess returns differ, since for example some fund evaluation agencies such as Morningstar use their own selection of benchmarks – hence indifferent to funds' official benchmarks. Clearly, for investors that use solely Morningstar in their fund selection process, the whole idea of benchmark changes on the fund level becomes meaningless.

Another natural concern relates to the insignificant performance ranking variables in Table IX. The most obvious possible explanation for this is that the length of the sample size is too narrow; most previous authors examine data sets with lengths around ten years. The market condition during our sampling period was bearish, and there is reason to suspect that the J-shaped relationship holds relatively poorly in this type of market. Furthermore, the Swedish market is dominated by large banks, and it has been found that bank-managed funds are less sensitive to past performance than other funds (Frye, 2001). The results could also be explained by that recent authors typically conduct separate rankings based on fund investment styles such as “value” and “growth”; however, we are unable to check for this cause due to limited data. To further investigate the relation between flow and performance in order to determine a potential difference between the US and Swedish markets is beyond the scope of this thesis but remains an interest topic of study.

We discovered that ethical funds on average change benchmarks more frequently than other funds do. In particular, they change more often to harder benchmarks, especially when they outperform their original benchmarks (see Table VI and Section V A2). In addition, ethical funds receive substantially more flow than normal funds which suggests that this effect should be controlled for hereafter in performance-flow regressions. These results can be seen in relation to articles e.g. by Bollen & Cohen (2005) and Horst, Zhang, & Renneboog (2006), who find that ethical funds are less sensitive to performance and fees since their investors have partly other objectives than profit maximization. In line with this, one could argue that reputation is of relatively larger importance to these funds. This view is supported by the fact that ethical funds are more frequent users of benchmarks that include dividends (see the part on descriptive statistics in Section III) – although the low partial coefficient in Table A III

suggests that this is driven by other factors. Should reputation be more important to ethical funds, then we indeed expect this type of funds to place larger concern on having an appropriate benchmark than presenting favorable figures on relative performance. Accordingly, the number of changes to easier in relation to changes to harder should also be lower for this group than for other funds. However, in the *bmdiff* regression in Section V B the *Ethical* variable showed up insignificant. This contradicts the hypothesis that ethical funds change more to harder benchmarks, unless the absolute values of the magnitude of changes to easier are larger than those for changes to harder which could imply that they offset the larger frequency of changes to harder.

From the logit regression we found that belonging to one of the four large banks in Sweden increases the probability of change to an easier benchmark and decreases the probability of change to a harder one. We may argue that the four large banks have a relatively high proportion of small-scale investors; most of who can be classified as part of the disadvantaged clientele in terms of knowledge in finance. These investors are likely to be more positively receptive to increases in the excess return due to benchmark changes and less keen on developing mistrust from the same practice, as long as it is not exposed negatively in the media; to our knowledge, the first media scope on the subject was in 2008 – hence outside our sample period. As a consequence, it can be relatively more beneficial for the large banks to change to easier benchmarks. Since the variable *MainBank* drops out in our fixed effects regressions, we re-estimate Model 2 and 3 with pooled OLS to spot any similar effect to that seen in Model 1. The coefficient comes out highly insignificant (although slightly negative) in Model 2 and positive but insignificant in Model 3. The same results are obtained from partial correlation coefficients: *MainBank* is significantly correlated with the direction of change (at a one percent level) but not with flow and the magnitude of change. The value of the partial correlation coefficient is 0.24 for changes to easier and -0.24 for changes to harder; among the variables in Model 1, only the coefficient of *ex_return_{old}* is larger. Just as for *Ethical*, a possible explanation for the difference in results between Model 1 and 2 is that funds belonging to the four main banks change more frequently to easier benchmarks on average but that changes to harder are larger in magnitude, thereby offsetting the smaller quantity.

Just as the American Securities and Exchange Commission (SEC), Swedish law does not regulate the choice of benchmark, which allows plenty of scope for funds to choose whichever benchmark they personally find appropriate. Nevertheless there could be external factors causing benchmark changes. Although we excluded funds that changed benchmarks due to strategy changes and mergers and acquisitions, one can question our results with the argument that still these exclusions do not provide enough filtering of distorting causes influencing benchmark change decisions. For instance, a benchmark change can follow a change in the asset composition of a fund even though explicitly the fund does not change strategy. This is especially true for mixed funds that make bets through asset allocation decisions, and we have accordingly put less effort in analyzing benchmark changes for this group. For mixed funds, we can also see a higher correlation between the new benchmark and the fund versus than that of the old benchmark; for the yearly return the Pearson correlation is 0.96 as opposed to 0.92. The corresponding difference for equity is 0.93 versus 0.91, suggesting that the returns of the new benchmark are somewhat more similar to the fund than the returns of the old benchmark are. There is also a similar small effect on the betas between funds and their old and new benchmarks.

We chose not to speculate too much on the cause of any particular external events on our results. We see that considerable differences between years exist in terms of benchmark change patterns, however. Two major events that occurred during the sample period are the stock market crash and the implementation of the pension reform in 2000 (the so-called PPM system). Furthermore, in 2003 in the fixed income market, interest rates were on an all-time low, and the pension and mutual fund management firm Skandia was troubled by a media scandal. These events are likely to affect both flows and benchmark changes. The Swedish Investment Fund Association (2004) for instance, estimates an increase in flows in 2000 by roughly 36 billion SEK due to the implementation of the PPM scheme (equivalent to 36 percent of total flows in that year). In the same year, as can be seen in Figure 1, there was a large decrease in popularity of the AFGX index and a corresponding increase in the use of the index SIX PX. To check whether our results are driven by these changes alone, we re-estimate our three regression models (Model 1-3) excluding the year 2000. Although this lowers the number of observations, it does not affect our conclusions as the coefficients are of the same direction and similar size.

The fact that the stock market exhibited a decline during our sample period (see Figure A 1) together with the common knowledge that funds take on more risk than their benchmarks in order to beat them, may explain why many funds underperform their benchmarks during our sample period (although as we mention earlier, this is not unusual). This in turn may explain why we see more changes to easier benchmarks and fewer changes to harder. Truly, we find that funds' relative performance affect the direction and magnitude of benchmark changes. Among the relatively few equity funds that outperform their benchmark, the majority change to harder benchmarks. Hence one can speculate that if more funds had outperformed their benchmark during our sampling period, perhaps there would have been a more even distribution of changes to easier and harder.

We wrote in the beginning that there exists no comparable published paper. However, in a forthcoming article to be published in the *Journal of Financial Economics*, Sensoy (2008) investigates benchmarks of American mutual funds. He finds that about thirty percent of equity funds use a benchmark that does not match the fund's investment style. Furthermore, the use of such mismatched benchmarks is relatively common among large and high-fee funds and does not seem to be attributed to chance. Nevertheless, the funds' performance relative to these inappropriate benchmarks affects flow. This leads the author to conclude that "at least some mutual fund investors may not be sophisticated enough to see through this when making decisions about purchases and sales of mutual funds" and this fact provides a potential strategic opportunity for funds to increase flow. Sensoy's findings and conclusions are clearly highly relevant to this paper and give support for our theory on benchmark changes.

Regarding our method to use one year returns and alphas one could argue that funds take longer periods into account for their change decisions. We mentioned in Section II B2 that a one year measure comes natural as it covers all new information available since the last period. During the robustness check for hypothesis one, we found that using two and five year performance measures yielded the same conclusion as previously, namely that funds change to easier benchmarks on average. We have also estimated flows quarterly, as in the paper by Sirri & Tufano (1998). This too did not affect the results much. One potential improvement however, could be to record benchmarks quarterly instead of yearly. Indeed, the assumption

that changes occur at year end is simplistic compared to the reality. From examining fund factsheets we can conclude that most benchmark changes cannot be attributed to any specific date. For those who report the date, it appears as if changes occur continuously over the four quarters of the year. Occasionally, as is the case for some Nordea funds, they change more than once annually. However, in most cases, the date for change is not recorded. Hence, to have recorded benchmarks quarterly would have eliminated more than half of the observations in our sample. Due to this reason as well as time-constraints and the fact that the factsheets we use are distributed after the completion of each year, we found it most practicable to assume that changes occur at the end of each year. For upcoming studies in the field, we nonetheless recommend the use of quarterly data as it provides a more accurate analysis. Moreover, although cross-sectionally our sample size is satisfying, we recommend authors using a similar approach to look at a longer time period (preferably more than ten intervals), as it allows more powerful statistical inference.

One may also criticize our focus on negative versus positive excess return – perhaps the benchmark changes follow a perfectly smooth function of the excess return that is only related to the magnitude of the measure? Indeed, this is an implicit assumption underlying Model 2, where a linear relationship is forced upon the ex_return_{old} variable. One could question whether the relationship really is linear, but we have no reason to suspect anything else and hence leave it to future papers to examine other types of relationships. A finding by Del Guercio & Tkac (2002, p 542) supports our fascination for negative and positive values of the excess return: for pension fund managers, beating a benchmark attracts a large lump sum of additional flow irrespective of the magnitude of the outperformance, as measured by the difference in returns. This phenomenon may be generalized and is in line with our theory; beating the benchmark does matter for funds, and adjusting the benchmark is a relatively easy way to do this.

VIII. Conclusion

This paper explores a new area in the academic field of mutual fund research. By gathering data on funds' official and specific benchmarks instead of applying a market index for all funds and all time periods, we obtain a unique and large sample which we inspect with various statistical techniques. We reach several interesting results in this process.

Firstly, there appears to be a tendency among funds to change to benchmarks with worse performance than their original benchmarks. Secondly, various characteristics affect the propensity of change, the likelihood that an easier or a harder benchmark is chosen, as well as the difference in returns between the new and old benchmark. In particular, funds performing badly in relation to their original benchmark have a higher tendency to switch to an easier benchmark whereas the opposite is true for funds that perform well. We believe that this is related to conflicting incentives of funds and fund managers to present at the same time both a favorable and an appropriate view of the performance of their funds to investors. At certain times and for certain funds, the benefits of changing to an easier benchmark may outweigh the risk of damaging reputation and trust among investors. One major, although not necessarily only, reason for funds to present good statistics to investors is that it affects investments in the fund, measured by net flows. Thirdly, in relation to this, we find positive effects on flow caused by benchmark changes. However, the results are puzzling as it appears as if change to harder benchmark has a larger positive effect than change to easier. Although speculative, this result may be partly driven by top performers that change to harder benchmarks and target sophisticated investors.

Our findings supports the view of an agency conflict between funds or fund managers on one side and investors on the other. Benchmark changes influenced by a fund's relative performance are not beneficial to investors, whereas it adds value to funds in terms of enhanced flow and perhaps also in terms of personal benefits of managers. This raises the question whether benchmark selections should be regulated by law; clearly, this could be of benefit to investors, but on the other hand, we find some evidence that reputation might to some extent serve the same function by deterring the use of benchmarks inappropriate for comparison.

Upcoming research may add to our findings by looking at longer time periods at shorter intervals on different data sets. So far, however, we provide a fundament for a new field of study, of relevance to academics as well as investors and fund management firms, and conclude by urging the common investor to pay close attention to the choice of benchmark next time they evaluate funds.

IX. References

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X. Appendix

Table A I
List of Primary Variables

The table shows the primary variables used for data analysis and in the construction of the secondary variables listed in Table A II.

Variable	Description	Source
<i>m_f_return</i>	Monthly fund net return; calculated as $NAV_t - NAV_{t-1}$	SIX Trust
<i>BMComposition</i>	Fund's benchmark composition as stated in factsheets	Factsheets
<i>m_i_return</i>	Monthly index return	Datastream, SIX Trust
<i>FIFundNumber</i>	Number appointed to funds by Swedish Financial Supervisory Agency; used e.g. to match TNA	Swedish Financial Supervisory Agency
<i>ISIN</i>	Fund ISIN	Factsheets
<i>FundName</i>	Fund name	Factsheets
<i>Huvudbolag</i>	Fund family registration number	Factsheets
<i>Manager</i>	The principal manager of the fund	Factsheets
<i>Type</i>	Whether the fund is equity, fixed income (bond and money market) or mixed fund	Factsheets
<i>EthicalType</i>	Whether fund applies ethical screening, and if so, what type	Factsheets
<i>SpecialFund</i>	Whether the fund holds a special status, e.g. that it is a hedge fund or index fund	Factsheets
<i>TNA</i>	Fund total net assets; reported quarterly by the Swedish Financial Supervisory Agency and yearly in factsheets	Swedish Financial Supervisory Agency, Factsheets
<i>TKA</i>	Totalkostnadsandel, total cost ratio (TER+transaction costs)	Factsheets
<i>TER</i>	Total expense ratio	Factsheets
<i>Turnover</i>	Annual fund turnover ratio	Factsheets
<i>StartDate</i>	The date the fund was launched	Factsheets

Table A II
List of Secondary Variables

The table briefly describes all secondary variables to be used throughout the paper. These variables were formed from the primary variables in Table A I.

Variable	Description
$return_{fund}$	Annual fund return; calculated geometrically from m_f_return
$StDev$	Annualized fund standard deviation; calculated over a two year period from m_f_return up to time t
bm_id	Benchmark ID assigned to each unique value of $BMComposition$
bm_all_ri	Dummy that is 1 if all indexes included in a benchmark are return indexes
bm_all_pi	Dummy that is 1 if all indexes included in a benchmark are price indexes
m_bm_return	Monthly benchmark return; calculated from m_i_return based on weights in $BMComposition$
$return_{new\ benchmark}$	Annual benchmark return calculated geometrically from m_bm_return
$StDev_{new\ benchmark}$	Benchmark standard deviation; calculated over a two year period from m_bm_return up to time t
$m_bm_return_{old}$	Monthly benchmark return for a fund's lagged bm_id
$return_{old\ benchmark}$	Annual benchmark return calculated geometrically from $m_bm_return_{old}$
$StDev_{old\ benchmark}$	Standard deviation of old benchmark; calculated over a two year period from $m_bm_return_{old}$ up to time t
$bmdiff$	Difference between $return_{new\ benchmark}$ and $return_{old\ benchmark}$
bm_change	Categorical variable that is -1 if $bmdiff < 0$, 0 if $bmdiff = 0$, and 1 if $bmdiff > 0$
$Change$	Dummy that is 1 if bm_change equals -1 or 1
$ChngEasier$	Dummy that is 1 if bm_change equals -1
$ChngHarder$	Dummy that is 1 if bm_change equals 1
ex_return_{new}	Difference between $return_{fund}$ and $return_{new\ benchmark}$
ex_return_{old}	Difference between $return_{fund}$ and $return_{old\ benchmark}$
α_{new}	Alpha calculated yearly on m_f_return and m_bm_return
α_{old}	Alpha calculated yearly on m_f_return and $m_bm_return_{old}$
$\alpha_{phadiff}$	Difference between α_{new} and α_{old}
bm_change_{α}	Categorical variable that is -1 if $\alpha_{phadiff} < 0$, 0 if $\alpha_{phadiff} = 0$, and 1 if $\alpha_{phadiff} > 0$
$Ethical$	Dummy for that is 1 if $EthicalType$ indicates that a fund applies screening
$Family$	Fund family; generated from $FundName$ and $Huvudbolag$
Age	Fund age; calculated as t subtracted by $StartDate$
$\ln TNA$	The natural logarithm of TNA
$\ln Age$	The natural logarithm of Age
$Flow$	Fund flow; calculated as $(TNA_t - TNA_{t-1}(1 + return_{fund,t}))/TNA_{t-1}$
$Flow_{real}$	Money fund flow; calculated as $TNA_t - TNA_{t-1}(1 + return_{fund,t})$
TNA_{Family}	Family TNA; calculated as the sum of fund TNAs for funds belonging to the same family
$FlowFamily_{real}$	Money family flow; calculated as the sum of $Flow_{real}$ for funds belonging to the same family
$FlowFamily$	Family flow; calculated as $FlowFamily_{real}/TNA_{Family\ t-1}$
$Mainbank$	Dummy that is 1 if a fund has $Family$ equal to SEB, Nordea, Handelsbanken, or Swedbank
$Rank$	Performance ranking variable that takes a value between 0 and 1 depending on a fund's performance in relation to other funds
$Star$	Dummy that is 1 if a fund is in the top 5 th percentile of $Rank$
Dog	Dummy that is 1 if a fund is in the bottom 5 th percentile of $Rank$
$strat_change$	Dummy that is 1 if a fund changed investment strategy
$Merged$	Dummy that is 1 if a fund merged
$Flowwin$	Winsorised $Flow$ where observations above 500 percent are set to the highest value just below the cutoff value

Table A III
Partial Correlation Matrix of the Use of Return Indexes

The table shows partial correlation coefficients with respect to the variable *bm_all_ri* for equity funds. This variable is a dummy that takes the value 1 if the indexes included in a benchmark for a fund incorporate all dividends and zero if they do not. The other variables are outlined in the first row. The number of observations is 792.

Variable:	<i>ex_return_{old}</i>	<i>Flow</i>	<i>StDev</i>	<i>Turnover</i>	<i>lnTNA</i>	<i>lnAge</i>	<i>TKA</i>	<i>Ethical</i>	<i>Mainbank</i>
Coefficient	-0.029	-0.009	0.062	0.040	0.082	-0.031	-0.133	0.052	-0.113
Significance	0.413	0.796	0.085	0.269	0.022	0.385	0.000	0.149	0.001

Table A IV
Development of Fees

Means of TKA per fund asset class and year are shown for the period 1999-2004. All funds that contain missing entries for TKA in any year during the period are excluded, which explains the low number of funds in the table (N).

TKA per type (%)	1999	2000	2001	2002	2003	2004	N
Equity	2.00	1.93	1.93	1.91	1.88	1.88	103
Fixed Income	0.79	0.71	0.68	0.66	0.67	0.67	21
Mixed	1.64	1.55	1.59	1.44	1.40	1.37	14
All	1.78	1.70	1.71	1.67	1.65	1.64	138

Table A V
Yearly Frequencies of Benchmark Changes

The table presents percentages of funds that change benchmarks, per fund asset class and year. N refers to the number of funds.

Benchmark changers per type (%)	2000	2001	2002	2003	2004	N
Equity	37	20	9.1	11	14	320
Fixed Income	4.7	16	4.3	1.5	6.3	86
Mixed	53	43	27	18	0	38
All	32	21	9.5	9.9	11	444

Table A VI
Standard Deviations of Funds and Benchmarks

This table shows mean standard deviations for funds, old benchmarks and new benchmarks, per fund asset class, for the period 2000-2004. The standard deviations were calculated on a 2-year rolling basis from monthly returns. The old benchmark is defined as the benchmark the fund would have if no change occurs.

Standard deviations (%)	Equity	Fixed Income	Mixed	All	Min	Max
The Fund	20.9	1.8	13.1	18.3	0.2	58
Old benchmark	19.9	3.2	10.6	17.2	0.2	33
New benchmark	18.7	1.9	11.0	16.3	0.2	31

Table A VII
Comparisons of Alphas of Benchmark Changers

The table contains annual Jensen's alpha measures of new and old benchmarks presented per asset class of investment. The alphas are calculated with monthly returns on the new and old benchmarks, respectively, where the old benchmark is the benchmark of a fund if it does not change (the original benchmark). Two tests are conducted to test whether the differences in mean and median alphas are equal, as opposed to the one-sided alternative that they are larger than zero. A p-value lower than 0.05 means that the difference is significant on a 5 percent level. The eight and ninth rows show the number of funds that change benchmarks in such a way that their new alpha is higher or lower, respectively, than their old alpha. The last row shows p-values for one-sided binomial tests of random outcomes, where the null hypothesis is equal and random binomial distributions. n_{higher_alpha} is the number of observations where $alpha_{new} > alpha_{old}$, and n_{lower_alpha} is the number of observations where $alpha_{new} < alpha_{old}$.

Mean alpha (1yr, %)	Equity	Fixed Income	Mixed	All	Min	Max
New alpha	-0.035	-0.057	-0.124	-0.050	-4.10	1.99
Old alpha	-0.214	-0.071	-0.068	-0.179	-3.64	1.87
Tests if $alphadiff > 0$:						
<i>T-test</i> (p-value)	0.000	0.420	0.806	0.000		
<i>Wilcoxon</i> (p-value)	0.000	0.177	0.205	0.000		
Frequencies						
Change to higher alpha	120	10	21	151		
Change to lower alpha	42	9	11	62		
Test if $n_{higher_alpha} > n_{lower_alpha}$:						
<i>Binomial test</i> (p-value)	0.000	0.500	0.055	0.000		

Table A VIII
Differences in Characteristics between Changers and Non-Changers

The table shows means of various fund characteristics for equity funds that do not change benchmarks and for equity funds that change benchmarks one or more times during the whole period 2000-2004. The fourth column shows a one-sided alternative hypothesis to the null hypothesis of equal means or medians of a particular variable for non-changers and changers. The fifth column shows the p-value from a matched-pair *t*-test of equality of means based on the hypothesis in the previous column, and the sixth column shows the p-value from a Wilcoxon signed rank test of equality of medians, with the same alternative hypothesis. The fund return and flow are measured in percent and over the whole five year period and are not annualized. All other variables are measured at the end of the period, which is in 2004.

	No changes	1 or more change(s)	H_i	T-test (p-value)	Wilcoxon (p-value)
Fund Return (5yr, %)	-4.2	-6.5	diff < 0	0.024	0.196
Standard Dev. (%)	16.8	14.5	diff < 0	0.000	0.003
Flow (5yr, %)	105	60	diff < 0	0.175	0.240
Size (TNA, SEK bn)	1.1	2.3	diff > 0	0.006	0.060
Age	9.0	12.0	diff > 0	0.000	0.000
Turnover	0.67	0.70	diff > 0	0.416	0.002
Fees (TKA, %)	1.91	1.79	diff < 0	0.218	0.115
Ethical (%)	9.1	20.6	diff > 0	0.042	0.042

Table A IX
Determinants of Benchmark Change Direction and Frequency;
Performance Measured by Alpha

The table shows robust estimates clustered by funds for two multinomial logit models where the main independent variable is α_{old} and the dependent varying. Only equity funds are included. Each model has two columns of coefficient estimates, one for outcome -1 and one for outcome 1. The base case is set to 0 (zero). The second and third columns present estimates from a model where the dependent variable is set as the categorical variable bm_change , which takes on the value -1 (change to easier) if $bmdiff < 0$, 0 (no change) if $bmdiff = 0$ and 1 (change to harder) if $bmdiff > 0$. $bmdiff$ is defined as the difference in one year returns between a fund's new and old benchmark. For the last two columns, the dependent variable is the categorical variable bm_change_{α} , which takes on the value -1 (lower) if $\alpha_{diff} < 0$, 0 (no change) if $\alpha_{diff} = 0$, and 1 (higher) if $\alpha_{diff} > 0$. α_{diff} is the difference between α_{new} and α_{old} , where α_{new} is a fund's Jensen's alpha calculated yearly on monthly returns of the fund and its new benchmark, and vice versa. The other explanatory variables are shown in the first column. *Flow* is the yearly net flows to a fund. *lnTNA* and *lnAge* are the natural logarithms of TNA and fund age, respectively. *StDev* refers to a fund's standard deviation. *Ethical* is a dummy that takes the value 1 if a fund applies ethical screening. *MainBank* is a dummy that takes the value 1 if a fund belongs to one of the banks SEB, Nordea, Swedbank, or Handelsbanken. The values in parentheses are the absolute values of the z-statistics. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent:	<i>bm_change</i>				<i>bm_change_{alpha}</i>			
Change Direction:	Easier		Harder		Lower		Higher	
<i>alpha_{old}</i>	-56.530***	(2.70)	66.173**	(1.97)	122.881**	(2.27)	-49.461***	(3.07)
<i>Flow</i>	0.197	(1.47)	-1.199	(1.56)	-0.239	(0.32)	0.107	(0.67)
<i>StDev</i>	-0.891	(0.46)	-3.276	(1.23)	-6.936**	(2.15)	-0.350	(0.20)
<i>Turnover</i>	-0.031	(0.09)	0.296	(0.96)	-0.252	(0.66)	0.110	(0.39)
<i>lnTNA</i>	-0.059	(0.53)	0.217	(1.57)	-0.116	(0.77)	0.010	(0.09)
<i>lnAge</i>	0.710**	(2.46)	1.029***	(2.74)	0.837*	(1.90)	0.865***	(3.07)
<i>TKA</i>	-14.780	(0.58)	-79.969**	(2.42)	-11.041	(0.28)	-35.872	(1.49)
<i>Ethical</i>	0.655**	(1.96)	1.686***	(3.68)	0.369	(0.63)	1.109***	(3.35)
<i>MainBank</i>	0.608**	(2.02)	-1.147***	(2.80)	-1.053*	(1.65)	0.414	(1.35)
<i>Year2000</i>	-0.833	(0.36)	-5.399*	(1.95)	-0.351	(0.11)	-1.937	(0.83)
<i>Year2001</i>	-2.244	(0.98)	-6.230**	(2.23)	0.413	(0.14)	-3.336	(1.44)
<i>Year2002</i>	-2.784	(1.25)	-8.227***	(3.01)	-0.774	(0.27)	-4.327*	(1.88)
<i>Year2003</i>	-2.750	(1.24)	-8.368***	(3.02)	-0.937	(0.35)	-4.297*	(1.87)
<i>Year2004</i>	-3.332	(1.50)	-8.827***	(3.21)	-2.563	(0.89)	-4.628**	(2.03)
<i>Observations</i>	771		771		771		771	

Table A X
Determinants of Magnitude of Change; Performance Measured by Alpha

The table shows the regression results from estimating fund and time fixed effect models with *bmdiff* and *alphadiff*, respectively, as dependent variables and the variables in the first column as explanatory. The regressions are conducted for both equity funds separately and all funds. *bmdiff* is defined as the difference in one year returns between a fund's new and old benchmark. *alphadiff* is the difference in alphas, calculated by subtracting Jensen's alpha of a fund based on its new benchmark with the corresponding alpha obtained from regressing the fund's monthly returns (during a one year period) on its old benchmark. The latter alpha is denoted α_{old} and is also the main independent variable in the models. *Flow* is the yearly net flows to a fund. *lnTNA* is the natural logarithm of TNA. *StDev* refers to a fund's standard deviation. The constant is the average value of the fixed effects. The values in parentheses are the absolute values of the t-statistics using robust standard errors clustered by funds. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Type of Funds:	Equity		Equity		All		All	
Dependent:	<i>bmdiff</i>		<i>alphadiff</i>		<i>bmdiff</i>		<i>alphadiff</i>	
α_{old}	1.890*	(1.91)	-0.428**	(2.34)	1.711	(1.63)	-0.405**	(2.15)
<i>Flow</i>	-0.005	(0.72)	0.000	(0.37)	-0.005	(0.71)	0.000	(0.35)
<i>StDev</i>	-1.025**	(2.00)	0.103**	(2.12)	-1.008**	(2.13)	0.097**	(2.44)
<i>Turnover</i>	-0.025	(0.53)	0.003	(0.72)	-0.010	(0.29)	0.002	(0.62)
<i>lnTNA</i>	0.030	(0.49)	-0.003	(0.53)	0.011	(0.20)	-0.001	(0.10)
<i>TKA</i>	11.401*	(1.79)	-1.496	(1.59)	8.463	(1.54)	-1.200	(1.42)
<i>Year2001</i>	0.051	(1.58)	-0.007***	(3.92)	0.050	(1.53)	-0.007***	(3.50)
<i>Year2002</i>	0.143	(1.61)	-0.018***	(4.12)	0.124	(1.50)	-0.015***	(3.58)
<i>Year2003</i>	0.001	(0.01)	-0.004	(0.68)	0.025	(0.39)	-0.006	(1.31)
<i>Year2004</i>	-0.033	(0.68)	-0.000	(0.07)	-0.043	(1.04)	0.001	(0.12)
<i>Constant</i>	-0.615	(0.49)	0.068	(0.58)	-0.201	(0.18)	0.017	(0.15)
<i>Observations</i>	122		122		150		150	
<i>R</i> ²	0.88		0.87		0.88		0.85	

Table A XI
Correlation Coefficients Matrix for Model 2

Pearson correlation coefficients are shown for the variables in the model described in Section V B1. The variables are the same as in Table IX.

	<i>bmdiff</i>	<i>ex_return_{old}</i>	<i>Flow</i>	<i>StDev</i>	<i>Turnover</i>	<i>lnTNA</i>	<i>TKA</i>	<i>Year2001</i>	<i>Year2002</i>	<i>Year2003</i>	<i>Year2004</i>
<i>bmdiff</i>	1.0000										
<i>ex_return_{old}</i>	0.3613	1.0000									
<i>Flow</i>	-0.1040	0.0547	1.0000								
<i>StDev</i>	-0.0866	-0.3932	-0.1324	1.0000							
<i>Turnover</i>	0.0328	-0.2179	0.0162	0.3824	1.0000						
<i>lnTNA</i>	0.1542	0.1526	-0.0664	-0.1407	-0.0855	1.0000					
<i>TKA</i>	-0.1903	-0.2459	-0.1302	0.1347	0.3845	-0.2546	1.0000				
<i>Year2001</i>	0.1663	0.0811	-0.0475	0.1241	0.0711	-0.0261	-0.0485	1.0000			
<i>Year2002</i>	0.0728	0.0412	-0.0909	0.4008	0.0018	-0.0259	0.0156	-0.2170	1.0000		
<i>Year2003</i>	-0.1656	-0.0485	-0.0413	0.2131	-0.0655	-0.0057	0.0233	-0.2546	-0.1772	1.0000	
<i>Year2004</i>	0.0059	-0.0109	-0.0247	-0.3900	0.0832	-0.0856	0.0757	-0.1928	-0.1342	-0.1575	1.0000

Table A XII
VIF Values for Model 2

The table shows Variance Inflation Factors (VIF) and Tolerance values for the variables used in the model in Section V B1. The variables are the same as in Table IX. The last column shows mean VIF.

Variable:	<i>lnTNA</i>	<i>StDev</i>	<i>TKA</i>	<i>Turnover</i>	<i>Year2001</i>	<i>Year2002</i>	<i>Year2003</i>	<i>Year2004</i>	<i>ex_return_{old}</i>	<i>Flow</i>	Mean VIF
VIF	12.44	11.79	9.99	2.94	2.04	1.68	1.61	1.39	1.25	1.08	4.62
Tolerance	0.08	0.08	0.10	0.34	0.49	0.59	0.62	0.72	0.80	0.93	

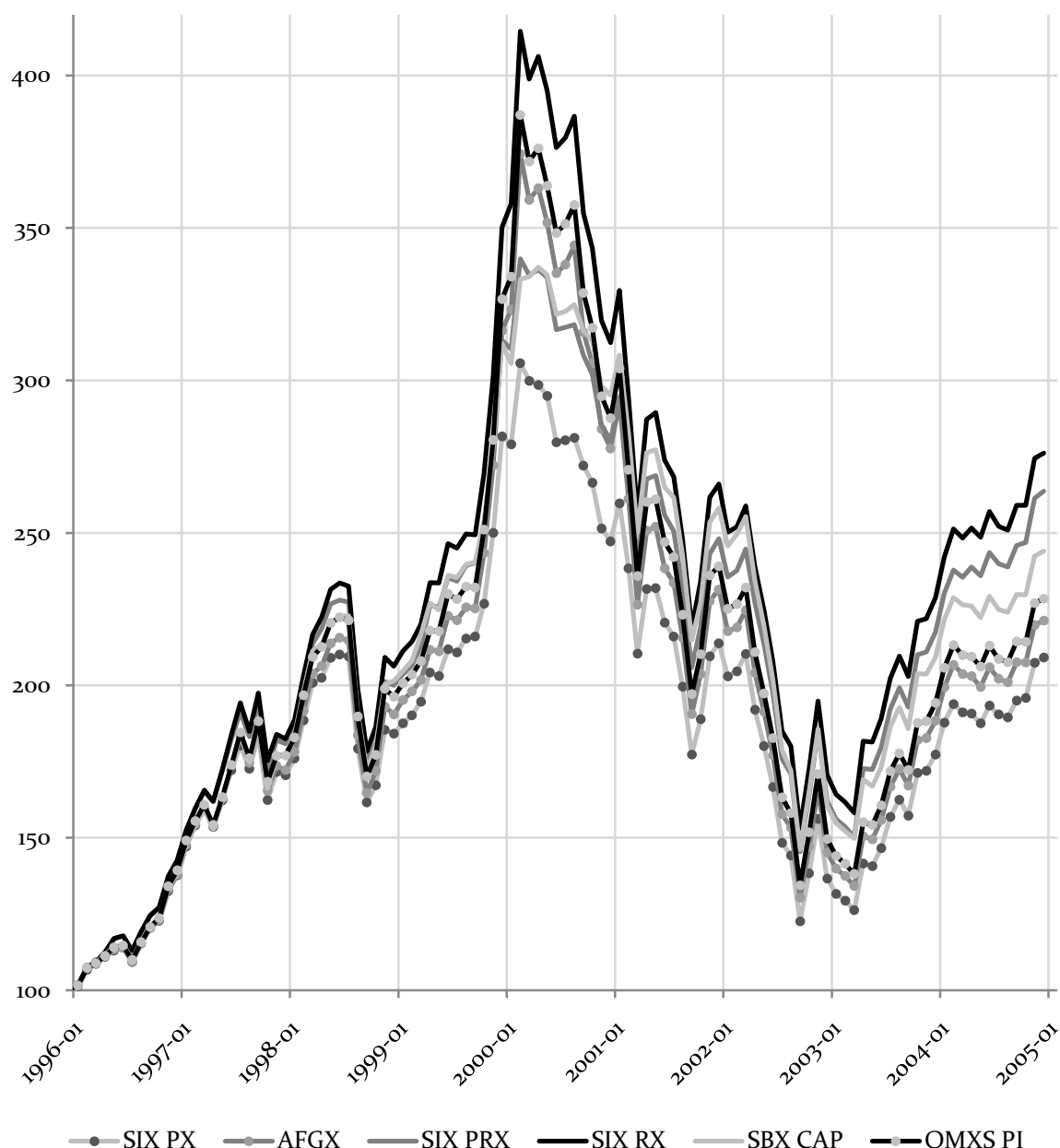


Figure A 1
Swedish Stock Index Developments

The graph shows the development of six common indexes covering stocks traded on the Stockholm Stock Exchange. The starting date 1995-12-31 is chosen as it is the earliest date for which all index series are available. The y-axis shows index levels where 1995-12-31 is set to 100 for all indexes. AFGX and OMXS PI are price indexes that cover all stocks traded on the exchange. SIX PX adjusts the AFGX by superimposing a maximum-weight restriction of 10 percent for any single stock in the index and SIX RX adjusts it by including dividends, whereas SIX PRX adjusts it for both these two features. SBX CAP comprises 80 to 100 of the largest and most frequently traded stocks on the exchange and furthermore imposes the maximum-weight restriction of 10 percent described above. SIX PX, AFGX, and OMXS PI are indexes excluding dividends, whereas SIX PRX and SIX RX include dividends. SBX CAP comes in two versions, one including dividends and one excluding – we here report the in our sample more commonly used variant that excludes dividends. In 2005, SBX changed name to OMXSB (OMX, 2005).