Available online at www.sciencedirect.com
SCIENCE DIRECT®
ELSEVIER
Journal of Banking & Finance 28 (2004) 673–694
Journal of BANKING & FINANCE
www.elsevier.com/locate/econbase

Data-conditioning biases, performance, persistence and flows: The case of Canadian equity funds

Richard Deaves

DeGroote School of Business, McMaster University, Hamilton, Ont., Canada L8S 4M4

Received 20 August 2001; accepted 20 December 2002

Abstract

This study constitutes the first comprehensive examination of Canadian mutual fund performance using a dataset free of all conditioning biases. The goal is to test many of the same hypotheses which have been previously addressed using US data. The sample is carefully constructed so as to avoid not only survivorship bias but also a form of backfilling bias that exists because funds have a timing option as to when to first provide results to information vendors. The deleterious impact of both forms of bias is documented. Not unlike what has been found in the US, on average fund managers net-of-expenses underperform benchmarks, but it also seems clear that their analysis and trading contribute to portfolio performance. I also present evidence that, at least on a short-term basis, success breeds success. Investors seem aware of this since money flows to successful funds. The strategy of chasing returns looks to be a viable one. One useful byproduct of this work is that an independent dataset has allowed for the corroboration of many of the same stylized facts that have been previously observed in the US.

JEL classification: G12; G20
Keywords: Mutual funds; Performance; Survivorship bias

1. Introduction

While in the US mutual fund assets have spiraled vertiginously, comparable growth in these Canadian intermediaries has been almost as impressive. In the last 20 years north of the 49th parallel net assets invested in mutual funds have grown

E-mail address: deavesr@mcmaster.ca (R. Deaves).

0378-4266/$ - see front matter
doi:10.1016/S0378-4266(03)00042-6

from below $2 billion (Canadian) to $400 billion. Academic research interest in the US has been rekindled not only by this market growth, but also because the view (after Jensen, 1968) that managers have no ability to outperform the market, even on a gross return basis, has been subjected to increasing scrutiny. Ippolito (1989) and Grinblatt and Titman (1989) marshaled in a change in thinking, suggesting that managers were in fact making a contribution, and were able to recoup for investors the expenses charged. Criticism centered on two fronts. First, the choice of benchmark was questioned. Elton et al. (1993) found the results of Ippolito evaporated once a benchmark was utilized that was more representative of the actual universe available to fund managers. More damning was the recognition that survivorship bias tainted many of the early studies. After correcting for this bias, Malkiel (1995), Elton et al. (1996a) and Gruber (1996) once again concluded that on average managers were not able to surpass passive risk-equivalent competitors net of (and sometimes even gross of) all expenses.

Another chink in the efficient markets armor however appeared around the same time. Even though the typical manager was not able to justify his costs, studies by Grinblatt and Titman (1992), Hendricks et al. (1993), Goetzmann and Ibbotson (1994), Gruber (1996) and Elton et al. (1996b) found convincing evidence that successful performance was not purely random. Managers who in a given period were able to outperform risk-adjusted benchmarks were more likely than not to repeat their success. The impact of survivorship bias and benchmark on persistence tests is more subtle. Brown et al. (1992) demonstrated via simulation that persistence can be overstated under certain circumstances. If fund volatility is constant over time but varies cross-sectionally, given that high volatility funds will tend to be toward the top if they survive the cut, their high volatility will also tend to put them toward the top in greater numbers in the evaluation period, thus overstating persistence. Nevertheless others (e.g., Grinblatt and Titman, 1992; Hendricks et al., 1993) have pointed out that a reversal effect can easily push the bias in the opposite direction. If fund survival depends on average performance over several periods, initial losers must improve in order to survive. The likely dominance of this latter effect is evidenced by the fact that persistence is typically weaker when using a sample of survivors rather than a full sample (see Hendricks et al., 1993). Moreover, Carpenter and Lynch (1999) simulate out an attrition effect: Poorly performing funds disappear so differences between top funds and bottom funds are understated. [1] As for the appropriate choice of benchmark, Carhart (1997) finds that when a factor model that includes a "momentum effect" is included, virtually all evidence in favor of persistence disap-

[1] Managerial game-playing may also skew persistence tests. At the time of writing, one of the major news stories in Canada's financial press (The Globe and Mail, 2000) was the revelation of "high-closing" manipulation undertaken by some money managers. To "juice" their numbers at year-end they sometimes pushed up the prices (by buying high) of their securities – thus inflating returns. Since prices can only temporarily be pushed up in this fashion, one might expect future returns to be lower as a result of such behavior. The end result is likely a bias towards detecting negative persistence. Also see Brown et al. (1996) for a volatility-seeking managerial stratagem.

pears – save for ill-performing funds. [2] Similarly, Daniel et al. (1997) conclude that a portfolio characteristic-based benchmark eliminates most persistence. Nevertheless some have remained convinced. Gruber (1996) argues that the choice made by some investors to entrust their money to successful active managers (also demonstrated by Sirri and Tufano (1998)) – once thought irrational – in fact is a rational one given that such "new money" has in the past been able to outperform the market. It was "old money," held by a "disadvantaged clientele" (either due to naivete or institutional constraints) that fell short, thus pulling down the overall average.

While these issues have been intensively investigated using US data, little research has been done on an international basis. [3] This may be because, as The Economist (1999) has recently said, while "Americans have a wealth of data about fund performance and costs at their fingertips…, old-worlders have to prostrate themselves before fund managers and beg for such information". In Canada however the range of data available and reporting requirements are not dissimilar to those in the US. This being so, it is puzzling that little research investigating Canadian mutual fund performance (and related issues) has been conducted. Most notably, Berkowitz and Kotowitz (1993), Kryzanowski et al. (1994, 1997) and Athanassakos et al. (1999), all using datasets subject to survivorship bias to varying degrees, generate conflicting results on performance. While Berkowitz and Kotowitz conclude that Canadian equity fund managers were able to earn excess returns after accounting for all expenses and loads, the other researchers found no evidence of significant managerial contribution or persistence. Given this incomplete and conflicting evidence, a comprehensive study investigating Canadian mutual fund performance (and related issues), and employing a dataset free of all conditioning biases, seems called for. Aside from the fact that Canadian researchers and consumers of mutual fund services should find such work of interest, US researchers will find it instructive as well. This is because it has the salient advantage of revisiting many of the same issues addressed in the US – but with a fresh data set. Though work in the US market often employs (somewhat) different data sources and looks at (somewhat) different time periods, much of it surely is taking different cuts at the same body of data. Moreover, though survivorship bias has been extensively documented in the US, to my knowledge no previous research has carefully quantified the impact of backfilling, another source of bias contaminating mutual fund databases.

This paper seeks to address these gaps. A sample of Canadian equity mutual funds for 1988–1998, which has been carefully constructed so as to avoid several data-conditioning biases, is used for this purpose. Other than the standard strain of survivorship bias which exists because information vendors usually drop defunct

[2] Grinblatt et al. (1995) find that successful funds utilize a momentum strategy, while funds that do not condition on this factor are not successful.

[3] Recent papers by Blake and Timmerman (1998), Dahlquist et al. (2000) and Otten and Bams (2000) have explored mutual fund managerial performance in a European context.

funds from their database, another strain – whose importance is here documented – is controlled for, namely a kind of self-selection cum backfilling bias that may be present when information is provided by companies to data vendors on a voluntary basis. [4] Given the lack of unanimity on appropriate benchmarks, several procedures are employed. First, a five-factor model that is designed to span the various sectors that Canadian equity fund managers invest in is used. As well as the three domestic sectors used in Elton et al. (1993, 1996a), the use of two offshore indexes is necessitated by the fact that most *Canadian* mutual funds are partly invested in non-Canadian assets. Second, a conditional CAPM technique (similar to Ferson and Schadt, 1996) is used. Finally, as a point of reference, a single-factor model is estimated.

Consistent with the US literature, three principal questions are asked. How does the typical mutual fund's performance compare to risk-adjusted benchmarks? In particular, net-of-expenses, can the average fund at least keep up to the market thus justifying the fees paid? Also, does a "hot hand" phenomenon exist? Are managers who rank high in the table more likely to do so in the future more than mere randomness would imply? Finally, what factors induce fund growth? How important is past performance? Do other factors, such as expenses and fund age, matter? Section 2 discusses both the assembly of the sample of mutual funds and the choice and operationalization of asset pricing benchmarks. In the next section I turn to typical performance. Section 4 investigates the existence of performance persistence. After considering in Section 5 the determinants of fund flows, Section 6 concludes.

2. Data and benchmarks

2.1. Constructing a bias-free sample

The mutual fund data used here were obtained from the *Financial Post Datagroup* in two forms. First, their main computer database was provided to the author. [5] Among other variables, total net assets and unit values were available on a monthly basis for virtually all mutual funds in existence in Canada. [6] In addition, certain scalars or one-time descriptive variables, such as the date of inception, fund type (e.g.,

[4] For somewhat related biases in the context of hedge funds, see Ackermann et al. (1999) and Liang (2000).

[5] I thank Frank Musselman and Mike Leung of the *Financial Post Datagroup* for help in obtaining and interpreting these data.

[6] These unit values, which are net of all management fees and other expenses (such as transaction costs), are calculated assuming that all cash flows are immediately reinvested. In some cases, the funds split their units necessitating an adjustment in the unit values. This was easily handled since the *Financial Post Database* also provided the split dates and ratios. Based on these unit values, returns were easily calculated.

equity, money market, balanced, etc.), countries/regions invested, load type (if any) and the latest management expense ratio (MER) were obtainable from this source. Second, the (hardcopy) *Financial Post Mutual Fund Survey* was available on a quarterly basis from 1987 to the end of 1998. In addition to containing most of the same information as the database, this source also provided, among other things, time series for MERs and, in a qualitative sense, sales charges (loads). One convenient feature of the *Financial Post Database* is that it does not discard information on defunct funds once they have first appeared. This means that it is straightforward to avoid standard survivorship bias by tracking all funds for as long as they exist. My procedure was to designate a fund as "alive" in a given year if it existed for the entire year under consideration. [7]

Given the voluntary nature of data provision, [8] it was suspected that a backfilling problem might exist. [9] Let us review the issue at hand. Suppose a company launches two funds at year-end 19xx; call them *A* and *B*. Over 19xx+1, *A* performs better than its risk-adjusted benchmark; *B* worse. The company decides to let *B* "die" by merging it with *A*. This is all done before either fund's records have been sent to the *Financial Post Datagroup*. Self-selection exists in that, when the company finally sends its data in, the full record for *A* is sent (19xx to the present), while *B* is omitted. The problem of course with using funds such as *A* is that we know that they are likely to have outperformed their defunct brethren *up to the point* when a choice is made to let *B* die and to send *A*'s (backdated) records in. An obvious potential for upward performance bias therefore exists.

The solution is to fall back on the hardcopy *Survey*, which signals the date of information release. *A* is included in the sample but *only after* it has appeared in the *Survey*. [10] More specifically, my procedure for deciding on the *first* observation of a fund in the sample was as follows. I began with all funds in the "Canadian equity funds" section of the *Survey* at the end of each calendar year (beginning with the December 1987 *Survey*) and, if they still existed at the end of the next year (according to the *Survey*), I included them in my sample for that year. [11] Once this

[7] Admittedly this procedure (as opposed to more problematic monthly sampling) will retain some slight survivorship bias.

[8] Conversations with the individual entrusted with organizing the database made it clear that all data were provided by the fund companies themselves to the *Financial Post* on a voluntary basis.

[9] One procedure would be to arbitrarily discard the first *x* observations (see Ackermann et al., 1999). Though certainly a less painstaking approach than that used here, it is clearly also less satisfactory.

[10] From this point on there is no a priori reason to believe that its performance will be either better or worse than other funds. As examples of the importance of this hardcopy screen, ignoring it would have led me to include the following funds *in my full 1988–1998 sample* instead of just the years indicated: *Green Line Blue Chip Equity* (1994–1998), *Marathon Equity* (1994–1998) and *Spectrum United Canadian Equity* (1993–1998).

[11] I dropped from the sample funds index funds, resource funds and narrow sectoral funds – plus several that were clearly misplaced. In addition, those that "wandered" to another category at some point (e.g., to the "balanced funds" category) I dropped believing there was a high probability that even when they were in the "Canadian equity" category, they perhaps did not really belong there in terms of portfolio composition and fund goals.

Table 1
Fund statistics: size of sample over time and mortality rates

Year	No. of funds in sample	No. surviving till end	Cumulative mortality rate (%)	Average mortality rate (%)
1988	110	70	36.36	4.42
1989	126	83	34.13	4.53
1990	134	97	27.61	3.96
1991	142	107	24.65	3.96
1992	148	116	21.62	3.98
1993	158	133	15.82	3.39
1994	174	154	11.49	3.01
1995	198	175	11.62	4.03
1996	207	192	7.25	3.69
1997	241	234	2.90	2.90
1998	300	–	–	–

Notes: The cumulative mortality rate is the percentage of funds that do not survive to the end of 1998; the average mortality rate is the compounded average of the latter figure.

control had been accomplished, the actual extraction of data was done using the database.

Using this approach for sample construction, as Table 1 shows, the number of funds in the sample begins at a low of 110, gradually rises to 207 by 1996 and then takes off to reach 300 by the end of the sample. Since the typical annual mortality rate of funds was on the order of 3.5–4.0% per year, this should alert us to the potential importance of survivorship bias. [12] I document below that this is indeed an important factor to correct for. In addition, I illustrate that uncorrected backfilling bias will also do damage.

2.2. Benchmarks

Given the lack of unanimity in the literature on what constitutes the appropriate asset pricing model, it was decided to employ several techniques for generating ex ante returns. First, a standard single-factor model was estimated as follows:

$$\mathrm{ER}_{i,t}^{(1)} = R_{i,t} - b_{M,i}R_{M,t}, \tag{1}$$

where $\mathrm{ER}_{i,t}$ is the estimated excess return for fund i at t; $R_{i,t}$ is fund i's return at t net of the T-bill rate; $R_{M,t}$ is the market's return at t net of the T-bill rate; and $b_{M,i}$ is fund i's beta versus Canada's standard market index, the *TSE 300*. [13] Averaging these excess returns over the estimation period yields (an estimate of) alpha.

[12] The overall average of these compounded average mortality rates is 3.8% per year. See Brown and Goetzmann (1995) for a probit analysis of the determinants of fund disappearance.

[13] The *Toronto Stock Exchange 300* is a value-weighted index of 300 medium- to large-sized Canadian companies. Betas were re-estimated each year, as were the other benchmark models presented here.

Using this single-index model, mean beta ranges from 0.75 to 0.91, with an overall average of 0.82. To obtain some perspective, Gruber (1996) finds that the average US equity fund beta in his sample is 0.96. First, it is not surprising that beta is below one since managers generally must keep some "cash" on hand to be prepared for unexpected redemptions. There is another factor at work in the Canadian context. The typical Canadian equity fund did not invest exclusively in Canada. It seems that the policy of the *Financial Post Datagroup* was to include funds in the Canadian equity category provided the offshore percentage did not reach a certain threshold. Between 1988 (at year end) and 1991 the average offshore investment percentage was 4.6%. With the phasing in of a new foreign investment RRSP-eligible percentage after this time (completed by 1994), this average increased (during 1992–1998) to 7.7%. [14] This serves to partly explain the rather low-mean betas. At the same time, it reinforces the appropriateness of using a model that takes into consideration offshore investment.

Given these considerations it was deemed appropriate to investigate a multi-factor approach with some foreign asset exposure. Moreover, even in a purely domestic context, the single-index model is increasingly viewed as inadequate. One reason for this is that, unless stock returns are generated by a single factor, it is unlikely that any arbitrarily chosen well-diversified portfolio will be mean–variance efficient. Increasing the number of indexes improves the probability of obtaining a benchmark on the efficient frontier (Grinblatt and Titman, 1987). Factor analysis can be employed here (e.g., Lehmann and Modest, 1987); or one can a priori identify a set of likely indexes (e.g., Carhart, 1997; Elton et al., 1993; Gruber, 1996); or some combination can be attempted (Elton et al., 1999).

I use here an extension of the Elton et al. (1993) sectoral approach. In addition to using the mid- to large-cap *TSE 300*, on the domestic front I also utilize a proxy for a Canadian small-cap index and a Canadian bond market index. Moreover, as mentioned above, the nature of the Canadian mutual fund market place necessitates the use of several offshore factors. This is because many managers of so-called Canadian equity funds actually invest a small percentage of their assets abroad, both in the United States and elsewhere. Therefore in addition I also employ as sectoral factors the S&P 500 and the Morgan Stanley World total return indices. Thus my second methodology for generating excess returns is based on

$$\mathrm{ER}_{i,t}^{(2)} = R_{i,t} - b_{M,i}R_{M,t} - b_{S,i}R_{S,t} - b_{B,i}R_{B,t} - b_{US,i}R_{US,t} - b_{W,i}R_{W,t}, \tag{2}$$

where $R_{S,t}$ is the small-cap net return at t; $R_{B,t}$ is the Canadian bond market's net return at t; $R_{US,t}$ is the Canadian dollar-converted S&P 500's net return at t; $R_{W,t}$ is the

[14] The Registered Retirement Savings Plan (RRSP), a tax-sheltered investment program, is subject to foreign investment upper limits. These changed from 10% to 20% mid-sample. Many Canadian funds strive to be "RRSP-eligible".

Canadian dollar-converted Morgan Stanley World index's net return at t; and $b_{S,i}$, $b_{B,i}$, $b_{US,i}$, and $b_{W,i}$ are the associated sensitivities. [15]

Of course one reason that researchers see the need to move to multiple factors is the rejection of unconditional CAPM by Fama and french (1992). Another approach is to allow CAPM's parameters to be time-varying. Jagannathan and Wang (1996) estimated a conditional version, and, by using an aggregate portfolio that incorporated human capital, succeeded in reversing Fama and French's rejection of CAPM. As an additional risk-adjustment procedure I use (after Ferson and Schadt, 1996) a linear operationalization of conditional CAPM, as follows:

$$\mathrm{ER}_{i,t}^{(3)} = R_{i,t} - b_{M,i}R_{M,t} - g_i' z_t R_{M,t}, \tag{3}$$

where g_i is a vector of sensitivities to z_t, a vector of instruments. To choose appropriate instruments, for all funds in the sample with data going as far back as the beginning of 1983, I estimated for 1983–87 a conditional CAPM model with Ferson and Schadt's (1996) five instruments (lagged T-bill rate, lagged market dividend yield, lagged term structure slope, lagged quality spread and a January dummy) plus two other likely candidates (lagged market volatility, proxied as a 12-month moving standard deviation of market returns, and lagged exponentially smoothed real market movements (as in Ilmanen, 1995)). [16] This group was pruned down to three (January dummy, dividend yield and quality spread) for performance assessment. [17]

[15] The Canadian bond index used was the *Scotia Mcleod* Canadian universe bond index (provided by Melanie Moore). This is a broad index including both governments and corporates. A number of inquiries made clear to the author that no small-cap Canadian index existed for the relevant sample period – although S&P has recently launched the "S&P/TSE Canadian Small Cap Index". In place of a small cap index, I used the very broad *Canadian Financial Markets Research Centre* (CFMRC) value-weighted index (which comprises several thousand companies and includes small- as well as large- and medium-cap companies). My two international indexes were the well-known S&P 500 and the Morgan Stanley World Index. After Elton et al. (1993), I employed the procedure of sequential orthogonalization. Beginning with my small cap proxy, I first regressed returns of the latter (net of T-bills) on net TSE 300 returns. (It can be shown that the surprises so generated are proportional to the surprises generated by a comparable regression of a hypothetical small-cap index on the TSE.) In estimating (2), I used these orthogonal surprises *plus the regression intercept* in place of the small-cap raw net returns. The third right-hand-side variable, the bond returns, was constructed by regressing the raw net bond returns on net TSE 300 returns and net small-cap returns, and the surprises plus the intercept were used in place of the raw net bond returns. The two international indexes were treated in the same sequential fashion. It can be shown that this process of sequential orthogonalization will generate the same alpha as would be obtained from (2) were we to use the unorthogonalized indexes. This remains true even if our indexes are overlapping in the sense that the CFMRC includes medium- and large-cap as well as small-cap, and the Morgan Stanley World Index encompasses both North America as well as the rest of the world.

[16] For 40% of the funds, joint significance of the instruments could be concluded at 5% using Wald tests.

[17] The other instruments had fewer significant t-statistics in the individual fund regressions and often the incorrect sign. Nevertheless, results were quite robust to the use of alternative instrument sets.

3. Average performance

3.1. All funds

Were Canadian equity fund managers able to surpass or at least keep pace with market benchmarks during 1988–1998 net of all expenses? The focus here is purely on the mean manager, so I do not consider, as in Chevalier and Ellison (1999), cross-sectional differences in behavior and performance. Performance was gauged using a single-index model, a five-factor model, and a version of conditional CAPM. Table 2 presents information on the performance of a typical fund both for each year in the sample, and for the entire 1988–1998 sample period. For individual years, mean performance is measured both using a simple average of all fund alphas and a net asset value-weighted average. It is important to account properly for the cross-sectional correlation in the fund alphas. [18] For individual years, since a common sample exists, I use a covariance matrix that controls for this cross-sectional correlation (see Elton et al., 1993). For the overall results, given that there exists a shifting sample–but one with sufficient monthly observations, I simply average out over the full sample the cross-sectional average monthly alphas, thus by construction eliminating the cross-sectional correlation problem. [19]

For individual years, the performance metrics using the five-factor, single-factor and conditional CAPM approaches are broadly consistent. For each proxy, seven out of the 11 mean alphas are negative. All cases of statistical significance are for negative alphas – though, given the high degree of cross-sectional dependence and the fact that each estimate is based on only 12 time series observations, most of these cases are only at the 10% level. Turning our attention to the last two rows of the table, it is apparent that on average Canadian equity funds fell short of the market on a risk-adjusted basis. Depending on our benchmark and whether we look at unweighted or weighted alpha, the monthly shortfall ranged from 7.3 to 13.3 basis points, or, annualized, 0.88–1.61%. [20] In four out of six cases this was significantly different from zero at 5%.

For a subsample of funds I constructed a time series of MERs using the *Financial Post Survey*. [21] The mean MER (for this group of funds) increased from a low of 1.59% (in 1988) to a high of 2.00% (for the last 2 years). Thus, while on a net-of-expenses basis the funds collectively fell short of their benchmarks, it is apparent that managers did provide some value. That is to say, managers were able to make a

[18] It has been suggested that the cross-sectional dependence of fund returns occurs as managers tend to adhere to a limited number of styles (see, for example, Grinblatt and Titman, 1992).

[19] This procedure allows us to calculate the significance for the weighted average alpha as well. Note that this approach would not work well for the individual year results since the average would be based on only 12 observations.

[20] Given the recent evidence of Edelen (1999) that managers are forced to engage in performance-reducing liquidity trading, these shortfalls are likely overstated.

[21] These were 64 of the 70 funds that existed throughout the entire 1988–1998 period. Six were dropped because of frequent missing MER data.

Table 2
Fund performance: average fund alphas using five-factor, single-factor and conditional approaches

		Five-factor alpha		One-factor alpha		Conditional CAPM alpha	
		Mean (% per month)	*P*-val	Mean (% per month)	*P*-val	Mean (% per month)	*P*-val
1988	*U*	−0.202	0.414	−0.255	0.603	−0.293	0.423
	W	0.188		0.135	0.000	0.053	
1989	*U*	−0.284	0.062	−0.344	0.135	−0.361	0.073
	W	−0.366		−0.364	0.000	−0.317	
1990	*U*	−0.368	0.057	−0.341	0.278	−0.357	0.237
	W	−0.328		−0.347	0.000	−0.364	
1991	*U*	−0.155	0.649	−0.016	0.968	−0.104	0.751
	W	−0.063		−0.184	0.000	−0.327	
1992	*U*	0.190	0.495	0.185	0.809	−0.001	0.998
	W	−0.064		0.099	0.000	−0.007	
1993	*U*	0.564	0.422	0.450	0.618	0.250	0.723
	W	0.548		0.391	0.000	0.146	
1994	*U*	−0.447	0.000	−0.369	0.266	−0.436	0.094
	W	−0.417		−0.284	0.000	−0.302	
1995	*U*	−0.059	0.905	0.012	0.984	0.107	0.800
	W	−0.241		−0.159	0.000	−0.080	
1996	*U*	0.216	0.598	0.271	0.772	0.402	0.577
	W	0.017		0.017	0.000	0.089	
1997	*U*	0.194	0.722	−0.098	0.916	−0.156	0.848
	W	0.144		−0.173	0.000	−0.202	
1998	*U*	−0.917	0.232	−0.476	0.638	0.146	0.832
	W	−0.876		−0.369	0.000	0.093	
1988–	*U*	−0.115	0.020	−0.089	0.154	−0.073	0.142
1998	*W*	−0.133	0.004	−0.113	0.046	−0.111	0.015

Notes: U is unweighted and *W* is weighted; *P*-vals are levels of significance where the maintained hypothesis is that the average alpha is zero.

positive contribution to their portfolios via their use of informed analysis and trading activity, but it was not one-for-one with resources expended.

3.2. Impact of data-conditioning biases

Table 3 illustrates the impact of data-conditioning biases in distorting performance. Both standard survivorship bias and backfilling bias are investigated. Beginning with the former, for each year the sample is split into funds that survive to the end of the sample and those that do not. [22] For the full sample, the average difference between alphas of surviving funds and those that cease existence by the end is highly significant using unweighted average alphas for all three risk-adjustment techniques. The annualized impact ranges from 2.32% to 2.71%.

[22] The last year is omitted since by construction all funds in the sample for 1998 must survive till the end of the sample.

Table 3
Impact of data-conditioning biases: Performance differences between unbiased samples and samples subject to 1/standard survivorship bias and 2/backfilling bias

		Surviving vs. non-surviving fund alphas		Not-in-sample vs. in-sample fund alphas	
		Mean difference (% per month)	*P*-val	Mean difference (% per month)	*P*-val
Five-factor model					
1988–1997	*U*	0.223	0.000	0.239	0.000
	W	−0.039	0.398	0.163	0.001
One-factor model					
1988–1997	*U*	0.202	0.000	0.224	0.000
	W	0.177	0.025	0.179	0.001
Conditional CAPM					
1988–1997	*U*	0.191	0.000	0.203	0.000
	W	0.129	0.076	0.171	0.001

Notes: *U* corresponds to unweighted averages and *W* to weighted averages; *P*-vals are levels of significance where the maintained hypothesis is that the mean differences are zero.

Backfilling bias also matters. To review, information was voluntarily sent to the *Financial Post Datagroup* by the funds, and in a given fund's early years, it was likely that companies sometimes exercised a kind of timing option. In the second column from the right in Table 3, I calculate the mean difference between the average alpha of all funds for which data are available (but which are excluded from the sample at a given point in time because of my screening procedure) and the average alpha of all funds making it into the sample. [23] All differences are positive and highly significant. On an annualized basis, these differences range from 1.92% to 2.91%. As expected, the excluded funds – having already passed a kind of survival screen – outperform funds included in the sample. Clearly, on the basis of this evidence, there is strong evidence that the method of using the hardcopy *Financial Post Survey* as a screen was justified on the grounds of eliminating this form of bias.

The nature of these two biases is different in an important sense. Since funds drop out over time, the impact of survivorship bias for the 1988 results would be much more severe than for the 1997 results. This is due to the fact that 36.36% of funds that were in the 1988 sample did not survive to the end, whereas only 2.90% that were in the 1997 sample did not make it to the end. On the other hand the backfilling bias need not operate in this declining fashion. [24] To get a feel for the overall bias imparted by these two sources, let us consider results for 1988–1997 so that both sources of bias are present for all included years. The overall mean monthly five-factor alpha using all funds included in the sample was −42.21 basis points (annualized).

[23] More specifically, for each month averaging is done over all funds in the two groups, differences between the means of the two groups are calculated for each month, and then averaging is done over all the months in the sample.

[24] The number of excluded funds in a given year ranges from 12 to 45.

Dropping all defunct funds increases this value by 45.70 basis points, moving performance slightly positive. Finally, the difference between mean performance for all funds (including those excluded because of backfilling) and only those actually included in the sample was 32.45 basis points. Thus the *cumulative* bias was on the order of 75–80 basis points. Though not an enormous figure, it is far from inconsequential when so many inferences are border line.

4. Persistence

Probably the issue that has attracted the most attention in the latest research thrust has been persistence. There is much at stake at here, since if the average fund cannot even earn back its management expenses and transaction costs, given the availability of low-cost index funds, it seems to be an irrational investment strategy to entrust one's savings to actively managed funds. Tests here are conducted in two ways. First, similar to Goetzmann and Ibbotson (1994) and Malkiel (1995), funds are designated as winners/losers based on whether their alphas are above or below the mean for all funds. Table 4 provides evidence on the ability of alpha-successful/unsuccessful funds to continue to perform well/badly. Shown are the percentages of funds continuing in their categories and the associated *P*-values (with the maintained hypothesis being no ability to repeat performance). [25] We look 1 to 5 years ahead. There is very solid evidence of very short-term persistence for successful managers. Looking ahead 1 year, between 57% and 65% (depending on our benchmark) of the time successful funds repeat. In all cases the results are statistically significant in the 5% neighborhood. As for medium-term persistence, though the percentages are generally above 50%, nothing is close to significant. In the case of subpar performers, the evidence is again strong in favor of short-term persistence and very weak for medium-term. For 1 year in the future the repeat percentages ranged from 57% to 63%.

Table 5 reports on another test methodology (similar to Gruber, 1996). In the ranking year, funds are sorted into deciles on the basis of alpha-performance, and then differences between subsequent average decile returns are calculated. Given no managerial skill one would expect zero differences. I also report on the differences in alphas between the top half and the bottom half of funds. [26] Once again, the evidence is strong that short-term persistence exists for both successful and unsuccessful funds. For five-factor alpha the difference in the alpha-performance of the top 10% and the bottom 10% is a statistically and economically significant 13.70%. The top vs. bottom *t*-tests also yield weak evidence of medium-term persistence (namely for 3 and 4 years out). Oddly though, by 5 years out all differences have

[25] More precisely, I present time series averages of cross-sectional average percentages for individual year results, and the *P*-values are based on these time series. This procedure eliminates by construction the cross-sectional dependence problem.

[26] Carpenter and Lynch (1999) argue that *t*-tests of these differences are well-specified and powerful relative to alternative persistence-detection methodologies.

Table 4
Persistence percentages for winners and losers: percentage of funds that were previously winners/losers that continue to be winners/losers in subsequent years

		Years ahead				
		1	2	3	4	5
Five-factor model						
Winners	Repeat percentage	0.590	0.506	0.513	0.515	0.420
	P-val	0.040	0.759	0.431	0.688	0.157
Losers	Repeat percentage	0.618	0.579	0.574	0.561	0.489
	P-val	0.033	0.090	0.116	0.116	0.700
One-factor model						
Winners	Repeat percentage	0.574	0.478	0.533	0.534	0.434
	P-val	0.054	0.503	0.301	0.593	0.292
Losers	Repeat percentage	0.571	0.490	0.535	0.530	0.443
	P-val	0.144	0.739	0.393	0.433	0.264
Conditional CAPM						
Winners	Repeat percentage	0.653	0.508	0.562	0.555	0.442
	P-val	0.002	0.802	0.135	0.160	0.189
Losers	Repeat percentage	0.627	0.520	0.563	0.582	0.443
	P-val	0.014	0.532	0.162	0.016	0.133

Note: P-vals are levels of significance where maintained hypothesis is that repeat% is 0.5.

turned negative. In sum, it seems likely that Canadian money managers have some short-term and perhaps medium-term ability (or disability). This evidence is broadly consistent with that produced in the US, one difference being the somewhat stronger tendency reported here for medium-term persistence.

This evidence suggesting that it is wise to follow successful managers is stronger than one might at first think. Take the result that, according to the one-factor model, *only* half of all managers earning a positive alpha are able to do so in the following year. Clearly though the expectation of a zero alpha next period is still better than investing in index funds. [27] The reason is that even cheap index funds cost something. Moreover, for reasons that are not immediately clear, equity index funds in Canada are very expensive. Whereas, according to Gruber (1996), it was possible to find a good number of US index funds with MERs below 30 basis points (this group averaged 21.9 basis points for 1990–1994), such generosity did not extend to Canada. Referring to the *Financial Post Survey* for December 1998, and selecting all Canadian equity funds with "index" as part of their name, after excluding three dubious entries, the remaining 13 funds averaged a whopping MER of 1.51%. There was only a single fund with an expense ratio as low as 0.5%. [28] Since the cost of

[27] Given an approximately symmetric distribution for alpha and half of the funds above and the other half below, one would expect to see an overall average alpha of zero for these previously successful funds.

[28] This was the *Royal Canadian Index Fund*. It should be noted that Canada has SPIDER-like instruments called Toronto index participation units (TIPs) which are much cheaper than Canadian index funds. These follow a narrow index of 35 securities so they may not be for all indexers.

Table 5
Persistence using deciles/halves: Top decile vs. bottom decile or top half vs. bottom half performance differences in subsequent years

	Years ahead				
	1	2	3	4	5
Five-factor model					
Decile 1 vs. decile 10					
Mean difference (%/year)	13.70	6.11	5.76	1.89	−3.39
P-val	0.005	0.136	0.067	0.376	0.581
Top half vs. bottom half					
Mean difference (%/year)	4.52	1.87	2.20	0.48	−1.73
P-val	0.005	0.116	0.049	0.471	0.247
One-factor model					
Decile 1 vs. decile 10					
Mean difference (%/year)	8.62	−0.96	0.21	−1.07	−5.03
P-val	0.007	0.629	0.850	0.694	0.316
Top half vs. bottom half					
Mean difference (%/year)	3.30	−0.57	1.23	−0.25	−2.29
P-val	0.006	0.369	0.030	0.862	0.217
Conditional CAPM					
Decile 1 vs. decile 10					
Mean difference (%/year)	11.28	1.71	3.18	3.90	−6.93
P-val	0.003	0.228	0.137	0.047	0.144
Top half vs. bottom half					
Mean difference (%/year)	4.92	0.60	1.77	1.60	−2.07
P-val	0.001	0.453	0.033	0.061	0.156

Note: P-vals are levels of significance where the maintained hypothesis is that the mean difference is zero.

indexing should not really differ markedly from its US equivalent, one can only wonder how competitive the Canadian mutual fund marketplace is. [29]

5. Fund flows

5.1. What determines fund flows?

The evidence of the last section suggests that it may be rational for investors to "chase" returns. The purpose of this section is to ascertain whether fund flows are in fact induced by better than average performance. There is abundant evidence in the US context that investors do indeed so behave (see for example Gruber, 1996; Sirri and Tufano, 1998). Moreover, the response of investors appears to be asymmetric: while investors pursue good returns, they do not flee bad returns. In addition, some have argued that another logical determinant of fund flows should be fund

[29] A casual look at the numbers also suggests that the mean MER for all Canadian equity funds is substantially above the comparable US figure. Casual empiricism suggests that economies of scale are not the answer.

costs – in particular, expenses and/or loads (see Sirri and Tufano, 1998). It is not obvious however that costs should matter since returns are always reported net of all expenses so they already incorporate fund costs. High expenses without commensurate ability will lead to low returns.

To investigate these issues, I focus on all funds with a continuous history during 1988–1998. Of the 70 funds meeting this requirement, 64 remained after the removal of six due to missing MER observations. [30] The average fund in this group grew from an asset base at 1987 year-end of \$119 million to \$477million by 1998. Overall by the end of 1998 there were \$30.5 billion of net assets in these funds. These comprised about a third of the overall universe of Canadian equity funds at my disposal in terms of net assets. It is important to note that, for a given fund, asset growth occurs in two ways: by positive fund returns and by positive fund net inflows. Both of these factors have been quite important at times. Often growth has come in spurts, a tendency that is accentuated by the fact that the natural asset accumulation coming from returns and net inflows are positively correlated (with a correlation coefficient of 0.55). For example, the best natural asset accumulation year was 1993 (35%). This year also witnessed growth from net inflows of 16.6% (the second highest net inflow growth figure). [31]

The focus here is on what induces net inflows. These inflows, for fund i from $t-1$ to t, are calculated as

$$\mathrm{NIF}_{i,t} = \frac{\mathrm{NA}_{i,t} - (1 + \mathrm{TR}_{i,t})\mathrm{NA}_{i,t-1}}{\mathrm{NA}_{i,t-1}}, \tag{4}$$

where $\mathrm{NA}_{i,t}$ is net assets of fund i at t, and $\mathrm{TR}_{i,t}$ is fund i's *gross* return at t. Notice that fund growth by virtue of prior performance is excluded.

Since past returns are commonly reported in the business press and in fund literature, and it is taken as an article of faith among some mutual fund experts that past performance is predictive of future performance, it is natural that investors would be most influenced by this. In addition, I also consider as explanatory variables MERs, loads, age, size, and total risk. [32] The latter is proxied by a moving 12-month standard deviation of returns. Loads are rendered qualitative by an indicator variable where unity represents the existence of a potential load. [33] Therefore a functional relationship for $\mathrm{NIF}_{i,t}$ is likely along the following lines:

---

[30] Recall that the MER data were obtained by hand from various issues of the *Financial Post Survey of Mutual Funds*. In some cases the MER was noted as "not available". My approach was as follows. Whenever four or more MERs were not available I discarded the fund from *this* particular sample. On the other hand, whenever fewer than four observations were missing I used "back-extrapolation", namely using the next available MER for the missing value.

[31] For a macro perspective of fund flows (see Warther, 1995), and for a perspective from the standpoint of fund families (see Khorana and Servaes, 2000).

[32] Capon et al. (1996) present survey evidence that mutual fund investors consider many non-performance related factors in choosing their funds.

[33] There are several reasons for not using an exact load figure. First, loads may either be front-end or rear-end, and there is no meaningful way to compare the two types. Second, effective loads are often discounted by brokers from a maximum permissible value. Third, for the last several years of the sample, the *Survey* did not provide a specific figure, only noting the existence (potentially optional or deferred) of a front-end and/or rear-end load.

$$\mathrm{NIF}_{i,t} = f(\mathrm{Performance}_{i,t}, \mathrm{Performance}_{i,t-1}, \mathrm{MER}_{i,t-1}, \mathrm{Load}_{i,t}, \mathrm{NA}_{i,t-1}, \mathrm{Age}_{i,t}, \mathrm{SD}_{i,t-1}), \tag{5}$$

where $\mathrm{Age}_{i,t}$ is the age of the fund in years, and $\mathrm{SD}_{i,t-1}$ is the lagged standard deviation of fund returns (or alphas).

Next I run a series of annual-frequency regressions in order to explore the importance of these factors. The highlights are in Table 6. A pooled linear estimation technique where all funds share common coefficients is utilized. There is no attempt to uncover any sort of "ideal" or predictive equation. Estimation was done both for raw returns and alphas as performance proxies. It turns out that raw returns have more explanatory power than alphas, which is not surprising since most investors are unlikely to have the requisite knowledge base to calculate magnitudes such as alphas. Most variables are expressed in relative terms: new asset growth is net of that of the mean for the year; all return variables are net of the (unweighted) average return (or alpha) for the year; the standard deviation for a fund is deflated by the average standard deviation; and MER is net of the mean fund MER. Since it is not clear how long it takes investors to respond to past history, I use both lagged and contemporaneous performance as possible explanatory variables. Nevertheless it is important to realize that even much of a contemporaneous return (or alpha) is in effect "lagged," since it is accumulating over the full year during which fund inflows can occur.

Table 6
Fund flow regressions: Regressions of annual fund flows on performance and other possible explanatory variables

Ind. variables	Eq. (1)	Eq. (2)	Eq. (3)
Constant	0.783	0.443	−0.176
Ret SD lagged	$0.976	0.090	
Alpha SD lagged			
MER lagged	−0.027	−0.186	
AGE	−0.003	−0.003	
log(NA) lagged	$−0.174	−0.105	
Load dummy	0.184	0.045	
Return	*8.847	−0.032	0.544
Return-positive		*15.279	−7.085
Return-high			*17.506
Return-low			6.263
Return lagged	$2.813	0.717	
Return-pos lagged		3.913	
Return-high lagged			
Return-low lagged			
R^2	0.088	0.104	0.105
DW	2.23	2.23	2.23
SSE	4.409	4.019	4.000

Notes: Dependent variable is percentage net inflow relative to the mean; Statistically significant at 1%/5%/10% is denoted by */#/$.

Looking at Eq. (1), it seems that contemporaneous fund returns are the key drivers of fund inflows. On average a 1% return over and above that of a typical fund induced an 8.8% greater than typical increase in fund size. This result was highly significant. As might be expected, past positive returns, fund size and total risk were also marginally significant. Past positive returns also induced fund growth. Fund size entered with a negative coefficient since a given dollar infusion matters much more (in percentage terms) for a small fund than a big fund. The positive impact of risk is anomalous. One would of course expect high risk to be an attribute that investors would prefer to avoid. With Eq. (2) I begin to investigate a possible asymmetric response of fund inflows to fund returns. For both past and present returns piecewise regression is utilized, where relative returns are categorized as being above or below the mean for the year, and differentiated slopes in these ranges are accommodated. To interpret, for funds with contemporaneous returns below par, no exceptional fund growth (or contraction) occurred, but for funds with returns above the mean, growth was 15.28% in excess of typical fund growth, [34] a pattern very much consistent with what has been demonstrated using US data. [35] To a certain extent this may be understandable because of the existence of such market frictions as rear-end loads and automatic investment plans. Note that past returns (both superior and inferior), risk and fund size have now ceased being significant determinants. With Eq. (3), I restrict my focus to contemporaneous returns and now allow for four piecewise segments: more than one standard deviation below the mean; above the latter up to the mean; above the mean but below the mean plus one standard deviation; and above the latter. The evidence now points clearly in the direction of only truly outstanding funds eliciting an above average fund inflow. Below the one standard deviation above the mean level, the coefficients do not even necessarily have the right sign. [36]

One can argue that performance pursuit may well represent rational investor behavior. Since the evidence favors the ability of Canadian managers to maintain performance to a certain extent, and since it appears that one can do (slightly) better by chasing returns rather than indexing, Canadian investors who eschew personal active management may have collectively come to a well-reasoned conclusion. [37]

[34] This numerical interpretation of course sets the coefficient on contemporaneous returns to zero.

[35] The absence of negative flows for ill-performing funds may be partly due to the survivorship bias inherent in using a group of funds with a continuous 1988–1998 history, since non-surviving poor performers are likely to have witnessed greater outflows than surviving poor performers.

[36] I repeated Eqs. (1)–(3) using five-factor alphas in place of raw returns. The results were broadly similar though weaker. Moreover, as suggested by an anonymous referee, I also investigated the stability of the performance-flow nexus over time. For reasons not immediately clear, there does exist intertemporal coefficient variability. For example, focusing on Eq. (1), the impact on fund flows of (contemporaneous and lagged) performance is significantly greater during 1989–1993 than during 1994–1998. I am able to offer no compelling reason for this. That said, in a regression for 1994–1998 alone, contemporaneous returns still have a significant impact on fund flows.

[37] This is not the same as saying that investors successfully moved their money to funds that were about to perform well, an issue requiring further investigation. See Zheng (1998) for a discussion of this issue.

Table 7
Payoff from pursuing winners: mean alphas for groups of funds screened by prior performance

	All funds	Screen: 0.00 SDs			Screen: 0.25 SDs			Screen: 0.50 SDs			Screen: 0.75 SDs			Screen: 1.00 SDs		
	Mean alpha (%/year)	Mean alpha (%/year)	No. of funds	*P*-val	Mean alpha (%/year)	No. of funds	*P*-val	Mean alpha (%/year)	No. of funds	*P*-val	Mean alpha (%/year)	No. of funds	*P*-val	Mean alpha (%/year)	No. of funds	*P*-val
1989	−3.610	−2.067	67	0.000	−2.139	44	0.003	−2.535	27	0.009	−4.127	15	0.006	0.253	6	0.740
1990	−3.747	−2.014	75	0.000	−1.503	49	0.031	−0.373	26	0.742	0.231	12	0.914	3.374	5	0.428
1991	−0.007	1.221	71	0.119	2.256	54	0.019	3.932	37	0.002	6.142	23	0.001	8.064	16	0.001
1992	2.074	7.295	57	0.000	9.258	42	0.000	10.567	32	0.000	13.677	20	0.000	16.879	16	0.000
1993	6.761	17.440	51	0.000	23.689	32	0.000	26.530	27	0.000	35.548	18	0.000	43.616	13	0.001
1994	−4.006	−5.386	51	0.000	−5.171	36	0.000	−6.063	31	0.000	−7.693	21	0.000	−6.950	11	0.002
1995	−1.286	−0.646	99	0.296	−1.401	77	0.023	−1.095	58	0.139	−0.277	33	0.805	−0.163	20	0.913
1996	1.300	5.909	69	0.000	8.018	49	0.000	10.980	33	0.000	15.530	20	0.000	17.883	17	0.000
1997	2.148	5.417	83	0.000	5.704	62	0.000	6.519	40	0.001	5.152	27	0.048	6.978	23	0.009
1998	−3.396	−1.457	117	0.040	−0.224	85	0.794	0.419	64	0.701	2.143	46	0.098	2.457	36	0.099

Note: P-vals are based on maintained hypothesis that mean alpha is zero.

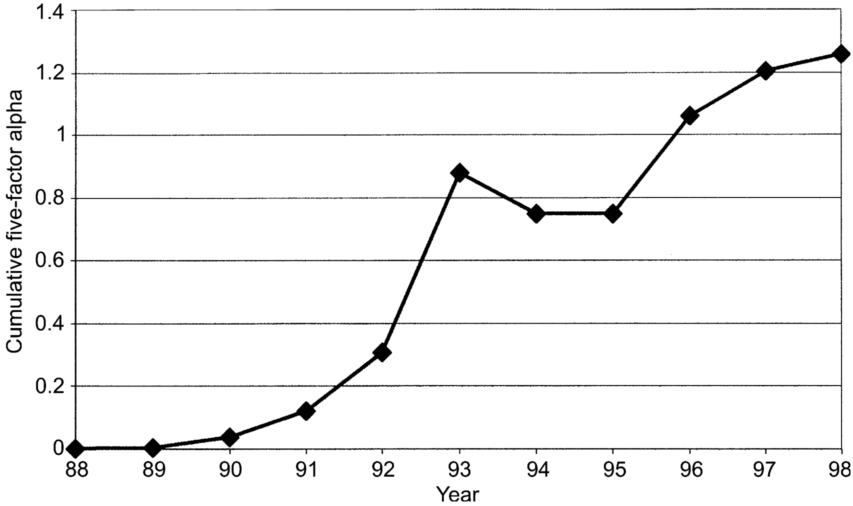

Fig. 1. Cumulative alpha from performance pursuit. (*Note:* Path above is generated by compounding average five-factor alpha for portfolios selected by the one standard deviation above the mean strategy.)

5.2. *Is performance-chasing investment a viable strategy?*

Clearly at least some investors chase performance. To ascertain whether this is a viable investment strategy, I performed the following analysis. At the end of every year, a portfolio of funds was selected on the basis of their alphas over the prior year. A number of screens were employed: the most inclusive was all funds with alphas above the mean alpha; in addition screens specified that a fund's alpha had to be 0.25, 0.5, 0.75 or one standard deviation above the mean.

Table 7 and Fig. 1 tell the story. In the table, again focusing on five-factor alpha, mean alphas for each year and the number of funds surviving the screen are provided. To interpret, if one focuses on 1998, based on performance history for 1997, 117, 85, 64, 46, or 36 funds were selected. The mean 1998 alphas were −1.46%, −0.22%, 0.42%, 2.14% and 2.46% respectively versus an average alpha for all funds of −3.40%. Overall, in the case of all screens, the strategy yielded an alpha in excess of the mean alpha for all funds at least eight out of ten times. The results for the finest screen are restated in the figure. Here I show the path of the cumulative five-factor alpha. Starting at the end of 1988, the investor purchases an equal-weighted portfolio of mutual funds. At year-end, all funds are redeemed, and another portfolio of funds is assembled. The curve shows the extent to which the gains or losses accrue over time. Using this screen throughout, one would have achieved an average compounded alpha of over 7%. Despite the fact that I assume no loads, switching fees or tax implications, [38] the evidence seems compelling that investors in Canadian mutual funds during 1988–1998 would have been able to profit from the ability of at least some managers to perform successfully on a consistent basis.

6. Conclusions

In this first comprehensive study of Canadian mutual fund performance, I arrive at a set of findings and conclusions reminiscent of Gruber's (1996). On average fund managers net-of-expenses underperform risk-adjusted benchmarks, but it also seems clear that their analysis and trading makes a positive (though not one-for-one with resources expended) contribution to portfolio performance. As earlier studies in the US have done before this one, the impact of survivorship bias is documented. Where my work departs from what has preceded it is in the identification of an additional data-conditioning bias for mutual funds, namely a self-selection cum backfilling bias that will be problematic whenever fund companies provide information on a voluntary basis to data vendors. It is likely that some commonly used US databases may fall prey to this same problem. [39]

While on average funds underperform, there is evidence that, at least on a short-term basis, success breeds success. Investors seem aware of this since money flows to successful funds. The latter relationship is not linear. While unsuccessful funds do not seem to suffer inordinately, highly successful funds attract the lion's share of new money. Finally it is documented that the strategy of chasing returns is indeed a viable one, and the best strategy of all may be to chase the funds that have performed best over the very near term.

Acknowledgements

The author would like to acknowledge the research assistance of Bruce Thomas and Steve Karan, and the helpful comments of two anonymous referees, as well as

---

[38] Many Canadian equity funds did in fact have loads (either front-end or rear-end) at the beginning of the sample, but there has been a proliferation of no-load funds over the last several years. Suggestive evidence can be provided from the last 3 years. If one had invested in the top three alpha-performing no-load funds in each of the last 3 years, one would have earned an average alpha of 10.2%. In each year at least two of the three funds so selected generated positive alphas.

[39] While it is true that mutual funds are regulated investment vehicles subject to reporting requirements mandated by legislation (such as the *Security Act* of 1933 and the *Investment Company Act* of 1940), provision of information on a voluntary basis to mutual fund information vendors is not regulated. Conversations with a number of representatives of three well-known US mutual fund database vendors suggested various possible forms of backfilling bias. First, two companies said their policy was to include data for all funds from inception – provided that *at least 6 months/1 year of history* existed, implying some backfilling bias. Second, as we have stated, a timing option exists as to when information of a voluntary nature is first sent in. As an example, an individual who looks after the database of one of these companies stated that there were a number of funds that began their lives in 2000 whose return data had only been sent in *during 2002*, and as of December 2002 their information was still in the process of being organized for inclusion in the database.

Carl Ackermann, Yisong Tian, Gordon Roberts, Michael Robinson, George Blazenko, Sarkis Khoury and Clas Wihlborg, and seminar participants at the 2000 Financial Management Association meeting, the 1999 Northern Finance Association meeting, Gothenburg University, York University, Carleton University, McMaster University and Rollins College.

References

Ackermann, C., McEnally, R., Ravenscraft, D., 1999. The performance of hedge funds: Risk, return and incentives. Journal of Finance 54 (3), 833–874.

Athanassakos, G., Carayannopoulos, P., Racine, M. (1999). Mutual fund performance: The Canadian experience between 1985 and 1996. Wilfred Laurier University, working paper.

Berkowitz, M., Kotowitz, Y., 1993. Incentives and efficiency in the market for management services: A study of Canadian mutual funds. Canadian Journal of Economics 26 (4), 850–866.

Blake, D., Timmerman, A., 1998. Mutual fund performance: Evidence for the UK. European Financial Review 2, 57–77.

Brown, S., Goetzmann, W., 1995. Performance persistence. Journal of Finance 50 (2), 679–698.

Brown, S., Goetzmann, W., Ibbotson, R., Ross, S., 1992. Survivorship bias in performance studies. Review of Financial Studies 5, 553–580.

Brown, K., Harlow, W., Starks, L., 1996. Of tournaments and temptations: An analysis of managerial incentives in the mutual fund industry. Journal of Finance 51 (1), 85–110.

Capon, N., Fitzsimmons, G., Prince, R., 1996. An individual level analysis of the mutual fund investment decision. Journal of Financial Services Research 10, 59–82.

Carhart, M., 1997. On persistence in mutual fund performance. Journal of Finance 52 (1), 57–82.

Carpenter, J., Lynch, A., 1999. Survivorship bias and attrition effects in measures of performance persistence. Journal of Financial Economics 54, 337–374.

Chevalier, J., Ellison, G., 1999. Are some mutual fund managers better than others? Cross-sectional patterns in behavior and performance. Journal of Finance 54 (3), 875–899.

Dahlquist, K., Engstrom, S., Soderlind, P., 2000. Performance and characteristics of Swedish mutual funds. Journal of Financial and Quantitative Analysis 35, 409–423.

Daniel, K., Grinblatt, M., Titman, S., Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. Journal of Finance 52 (3), 1035–1058.

The Economist, 1999. Aux armes, investisseurs. February 13, p. 73.

Edelen, R., 1999. Investor flows and the assessed performance of open-end mutual funds. Journal of Financial Economics 53, 439–466.

Elton, E., Gruber, M., Blake, C., 1996a. Survivorship bias and mutual fund performance. Review of Financial Studies 9 (4), 1097–1120.

Elton, E., Gruber, M., Blake, C., 1996b. The persistence of risk-adjusted mutual fund performance. Journal of Business 69, 133–157.

Elton, E., Gruber, M., Blake, C., 1999. Common factors in active and passive portfolios. European Finance Review 3 (1), 53–78.

Elton, E., Gruber, M., Das, S., Hlavka, M., 1993. Efficiency with costly information: A reinterpretation of evidence from managed portfolios. Review of Financial Studies 6 (1), 1–22.

Fama, E.F., French, K.R., 1992. The cross-section of expected stock returns. Journal of Finance 47 (2), 427–465.

Ferson, W., Schadt, R., 1996. Measuring fund strategy and performance in changing economic conditions. Journal of Finance 51 (2), 425–461.

The Globe and Mail, 2000. Signs point to mutual fund high-closing. July 5, p. B1.

Goetzmann, W., Ibbotson, R., 1994. Do winners repeat? Journal of Portfolio Management 20 (Winter), 9–18.

Grinblatt, M., Titman, S., 1987. The relation between mean–variance efficiency and arbitrage pricing. Journal of Business 60, 97–112.
Grinblatt, M., Titman, S., 1989. Mutual fund performance: An analysis of quarterly portfolio holdings. Journal of Business 62, 393–416.
Grinblatt, M., Titman, S., 1992. The persistence of mutual fund performance. Journal of Finance 47 (5), 1977–1984.
Grinblatt, M., Titman, S., Wermers, R., 1995. Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior. American Economic Review 85 (5), 1088–1105.
Gruber, M., 1996. Another puzzle: The growth in actively managed mutual funds. Journal of Finance 51 (3), 783–810.
Hendricks, D., Patel, J., Zeckhauser, R., 1993. Hot hands in mutual funds: Short-run persistence of relative performance, 1974–88. Journal of Finance 48 (1).
Ilmanen, A., 1995. Time-varying expected returns in international bond markets. Journal of Finance 50 (2), 481–506.
Ippolito, R., 1989. Efficiency with costly information: A study of mutual fund performance, 1965–84. Quarterly Journal of Economics 104 (1), 1–23.
Jagannathan, R., Wang, Z., 1996. The conditional CAPM and the cross-section of expected returns. Journal of Finance 51 (1), 3–53.
Jensen, M., 1968. The performance of mutual funds in the period 1945–64. Journal of Finance 23, 389–416.
Khorana, A., Servaes, H., 2000. What drives market share in the mutual fund industry? Dupree College of Management, Georgia Institute of Technology, working paper.
Kryzanowski, L., Lalancette, S., To, M., 1994. Performance attribution using a multivariate intertemporal asset pricing asset pricing model with one state variable. Canadian Journal of Administrative Sciences 11 (1), 75–85.
Kryzanowski, L., Lalancette, S., To, M., 1997. Performance attribution using an APT with prespecified macrofactors and time-varying risk premia and betas. Journal of Financial and Quantitative Analysis 32 (2), 205–224.
Lehmann, B., Modest, D., 1987. Mutual fund performance evaluation: A comparison of benchmarks and benchmark comparisons. Journal of Finance 42, 233–265.
Liang, B., 2000. Hedge funds: The living and the dead. Journal of Financial and Quantitative Analysis 35 (3), 309–326.
Malkiel, B., 1995. Returns from investing in equity mutual funds 1971 to 1991. Journal of Finance 50 (2), 549–572.
Otten, R., Bams, D., 2000. European mutual fund performance. Maastricht University, working paper.
Sirri, E., Tufano, P., 1998. Costly search and mutual fund flows. Journal of Finance 53 (5), 1589–1622.
Warther, V., 1995. Aggregate mutual fund flows and security returns. Journal of Financial Economics 39, 209–235.
Zheng, L., 1998. Is money smart? A study of mutual fund investors' fund selection ability. Journal of Finance 54 (3), 901–933.