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ESTIMATING SHORT-RUN PERSISTENCE IN MUTUAL FUND PERFORMANCE

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Estimating Short-Run Persistence in Mutual Fund Performance*

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Abstract

The purpose of this paper is two-fold. First, we analyze the properties of a number of estimators that can be used to estimate short-run persistence in mutual fund returns. When data for different funds are pooled, it is advisable to correct for cross-sectional differences in expected returns. However, these adjustments may induce biases in the estimated persistence coefficients and thus lead to spurious persistence. Theoretical derivations, combined with a Monte Carlo study, show that the importance of these biases cannot be neglected for the samples that are typically used in applied work, in particular if the number of time periods is small. Second, we estimate the short-run persistence in two samples of U.S. open-end mutual funds using quarterly returns for 1986-1994. The subsample of growth funds appears to have a persistence pattern that is quite similar to the one found by Hendricks, Patel and Zeckhauser [1993] for the period 1974-1988. In general, the results are quite sensitive to the estimation method that is employed.

Key words: Mutual Funds, Performance, Estimation Biases, Hot Hands.
JEL classification: G11, G23, C20.

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1 Introduction

The fast growing mutual fund industry tries to attract investors by advertising its past record of fund returns. Empirical evidence (see Patel, Zeckhauser and Hendricks [1992]) shows that investors are more willing to invest money in a mutual fund if the fund returns are high compared to other mutual funds. Apparently, these investors expect that mutual funds with above average returns in one period will continue to have above average returns. If this is indeed the case, an investment strategy based on identifying funds with so-called hot hands can increase the expected return on investors' portfolios of mutual funds.

While the efficient market hypothesis suggests that past returns are uninformative about future returns, recent studies find some statistically significant short-run persistence in mutual fund returns. Knowledge of such a pattern of predictable returns can be valuable, as shown by Hendricks, Patel and Zeckhauser [1993], who find that an investment strategy based on selecting mutual funds with an above average return in the last four quarters increases the expected return on a portfolio by 31 basis points over the next four quarters.

In this paper we examine a range of estimation methods used to detect patterns of predictable returns. As we shall see below, estimation errors in some of these methods may induce spurious findings of short-run persistence. However, the most severe bias we find is negative, indicating that it cannot generate a spurious finding of hot hands in mutual funds. Furthermore, we investigate whether a persistence pattern similar to the one found for the period 1974–1988 by Hendricks, Patel and Zeckhauser [1993] still holds for the period 1986–1995.

The remainder of this paper is organized as follows. In section 2 we present five methods, mostly proposed in the literature, to estimate patterns of persistence in mutual fund returns. For a finite number of periods, several of these methods can be shown to have an asymptotic bias in the estimated coefficients. In section 3 we derive analytical expressions for these biases, starting from the hypothesis that the returns on each fund are independent drawings from a time-invariant distribution. To simplify our expressions, we only consider the case where one lag is included in the persistence equation. For the general case, with a larger number of lags, we present additional results in Section 4 using a Monte Carlo study. The results from this study indicates that the analytical results from Section 3 are equally valid for other lags than the first one. In addition, we consider the case where fund returns do have a pattern of predictability and discuss to what extent the estimation methods are able to detect and estimate this pattern. Section 5 presents the results of an empirical study into the short-run persistence in a sample of open-end mutual funds, selected from the Morningstar database, over the period 1986 to 1994. Finally, section 6 concludes.

2 Persistence of Returns

Active selection among mutual funds can be profitable if mutual fund returns show a pattern of predictable behavior. If this is the case, the expected return on an investor's mutual fund portfolio can be increased if he is able to identify funds that will be superior performers in the future. For instance, if funds exhibit significant positive persistence in returns over a certain period then it can be worthwhile for an investor to select the funds with a high return, relative to their own unconditional mean return, over that period to increase the expected return on his portfolio. However, before we can test an economically valuable investment strategy, we first have to identify the form of the pattern of predictable returns.

For the moment, let us consider N mutual funds with an observed return history of T periods. Furthermore, we assume that the conditional expected return of mutual fund i in period t can be written as

$$E_{t-1}[r_{it}] = \gamma_{i0} + \sum_{j=1}^{J} \gamma_{ij} r_{i,t-j} = \mu_i + \sum_{j=1}^{J} \gamma_{ij}(r_{i,t-j} - \mu_i). \tag{1}$$

where r_{it} is the return in excess of the risk free rate and $\mu_i = E[r_{it}] = \gamma_{i0}/(1 - \sum_j \gamma_{ij})$ is the unconditional expected excess return. The coefficients γ_{ij} $(j = 1, ..., J)$ reflect persistence in the excess return of fund i, relative to its own unconditional mean. Clearly, the efficient market hypothesis implies that each parameter γ_{ij} is equal to zero. Recent empirical evidence (see Grinblatt and Titman [1992], Hendricks, Patel and Zeckhauser [1993], Goetzmann and Ibbotson [1994]) indicates that there may be some, statistically significant, short-run persistence in mutual fund returns. For example, Hendricks, Patel and Zeckhauser [1993] claim that the predictable behavior of mutual fund returns can be profitable for an investor who actively selects mutual funds according to certain investment strategies based upon funds' past returns.

Predictable behavior of mutual fund returns can be estimated using regression analysis, after rewriting (1) as

$$r_{it} = \gamma_{i0} + \sum_{j=1}^{J} \gamma_{ij} r_{i,t-j} + \varepsilon_{it} \tag{2}$$

where ε_{it} is the unexpected return of fund i in period t. In principle, (2) can be estimated for each of the N funds in the sample. However, usually one is not directly interested in the persistence pattern of an individual fund, but rather in examining whether a group of mutual funds has, on average, a pattern of predictable returns. Moreover, individual estimates are likely to be very inaccurate due to a small signal-to-noise ratio, particularly when the fund's history is short. Therefore, it is common to pool the returns of all funds and estimate a set of common persistence coefficients, or, when homogeneity of γ_{ij} is not imposed, estimate a set of – hopefully – average coefficients. In the sequel, we shall consider several approaches that are suggested for this purpose.

A first way to estimate short-run persistence of mutual fund returns follows Fama and Macbeth [1973] and is based on cross-sectional regressions of the form

$$r_{it} = k_t + \sum_{j=1}^{J} \gamma_{jt} r_{i,t-j} + u_{it}, \quad i = 1, ..., N, \tag{3}$$

where homogeneity of the persistence pattern over the funds is imposed, while variation over time is not excluded. This standard Fama-Macbeth procedure implies that (3) is estimated for each period t, after which parameter estimates, and standard errors, are obtained from the time series of regression estimates. In particular, the set of estimated slope coefficients is treated as a random sample from a population with constant mean γ_j. We shall refer to this approach as *FM*.

Essentially, (3) checks for autocorrelation in fund returns imposing that these are drawings from a distribution with a *common*, time-varying, mean. That is, the specification in (3) does not only impose that the predictability pattern is the the same for all funds, but also that the expected return on each of the funds is same. As argued by Jegadeesh [1990], this may lead to biased estimates for the persistence coefficients, because, relative to the common mean, fund returns do exhibit correlation over time, even if all γ_{ij} are zero. Intuitively, funds with a high average return are simply more likely to have high returns (relative to the common mean) in all periods. Given that there is variation in expected returns over the funds, estimating (3) by ordinary least squares will find spurious correlations over time between current and past returns.

Most solutions for this problem try to eliminate γ_{i0} or (equivalently) μ_i by subtracting some estimate of it from the left hand side variable. Denoting this estimate by $M_{t-1}(r_{it})$, the resulting cross-sectional regression is given by

$$r_{it} - M_{t-1}(r_{it}) = k_t + \sum_{j=1}^{J} \gamma_{jt} r_{i,t-j} + \tilde{u}_{it}, \quad i = 1, ..., N, \tag{4}$$

which can be estimated according the Fama Macbeth procedure. A number of different estimators of the unconditional expectation have been proposed in the literature (see Jegadeesh [1990], Hendricks, Patel and Zeckhauser [1993]). Let us consider three possible choices for M_{t-1},

1. $M_{t-1}(r_{it}) := \bar{r}^*_{i,t} = \frac{1}{S}\sum_{s=1}^{S} r_{i,t+s}$, the average return over period $t+1$ to $t+S$ for some positive S.

2. $M_{t-1}(r_{it}) := \bar{r}_i = \frac{1}{T}\sum_{s=1}^{T} r_{is}$, the average historical return over period 1 to T.

3. $M_{t-1}(r_{it}) := \hat{r}_{it} = b_{0i} + \sum_{k=1}^{K} \beta_i^k(\delta_{kt} - r_f)$, the return predicted by a linear K-factor model.

We shall refer to the estimation methods of equation (4) with the above specification of the unconditional expected return as *FM1*, *FM2* and *FM3*, respectively. While the first choice, corresponding to the one made by Jegadeesh [1990], indeed eliminates the bias due to variation in expected returns over the funds, the latter two, examples of the choices made by Hendricks, Patel and Zeckhauser [1993], generate another bias as we will show below, which may induce a spurious finding of negative short-run persistence in returns. A disadvantage of Jegadeesh' approach is that it requires returns over the period $t+1$ to $t+S$ to estimate the unconditional expected returns. In particular, when economically valuable investment strategies are investigated, this method does not seem very attractive because the number of time series observations available is often small.

As an alternative strategy, we suggest a different estimation method based on the analogy of removing fixed individual effects in a dynamic panel data model (see Hsiao [1985, p. 71 ff.], Baltagi [1995, p. 125 ff.]. In this approach, the returns over the N funds and T periods are pooled, after which the model is written in terms of first differences, while including a time-varying intercept. Although this eliminates the fund specific effects in γ_{i0}, it does lead to correlation between lagged returns and the error term, invalidating least squares estimation. Therefore, we follow Anderson and Hsiao [1981] and estimate the resulting equation

$$r_{it} - r_{it-1} = \gamma_t + \sum_{j=1}^{J} \tilde{\gamma}_j(r_{i,t-j} - r_{i,t-j-1}) + v_{it}, \quad t = 1, ..., T \text{ and } i = 1, ..., N \quad (5)$$

by instrumental variables. A valid instrument for $r_{i,t-1} - r_{i,t-2}$ is given by $r_{i,t-2}$, while all other regressors can be treated as exogenous and thus serve as their own instruments. We shall refer to this method as *pooled IV*.

The five estimation methods above all produce estimates for some average of the individual persistence coefficients over the funds, or for the common value of these coefficients when there is no fund heterogeneity in γ_{ij} ($j = 1, ..., J$). To show that some of these estimators may produce seriously biased estimates, we shall first, in the next section, derive analytical expressions for their probability limit when the number of lags in the regression is restricted to 1 ($J = 1$) and the true persistence coefficients are all equal to zero ($\gamma_{ij} = 0$ for all i). More general cases are considered in Section 4, on the basis of a Monte Carlo study.

3 Properties of the Estimators: Analytical Results

Deriving analytical expressions for the properties of the range of estimators discussed above in a very general case is tedious and does not provide much insight. Therefore, we simplify the analysis, and shall consider in this section the case where only one lag is included in the regressions ($J = 1$). For the moment, we shall also assume that the efficient market hypothesis holds, which implies that past returns do not have any indicative value for future returns. True fund returns are assumed to be generated by the following one factor model

$$r_{it} = \beta_i r_{mt} + \eta_{it} \tag{6}$$

where we shall refer to r_{mt} as the return on the market portfolio in excess of the risk free rate (although it may denote any other factor that prices the funds), and where β_i is the sensitivity of fund i with respect to the market portfolio. For a given fund i, the unobservable error terms η_{it} are assumed to be i.i.d. drawings from a distribution with zero mean and constant variance, independent of r_{mt}. Consequently, the data generating process (6) implies that the expected excess return on fund i, as defined in (1), is given by $\mu_i = \beta_i \mu_m$, where $\mu_m \neq 0$ is the expected excess return on the market portfolio. It also implies that $\gamma_{ij} = 0$ for all i and j. Although (6) may be somewhat restrictive, it serves our purpose as it implies that any excess performance is the result of luck (a good draw of η_{it}), and has no predictive power for future performance. The β_i's are assumed to be random drawings from a distribution with mean μ_β and variance σ_β^2, uncorrelated with η_{it} ($t = 1, ..., T$).

Let us first consider the OLS estimators for γ_{1t} in (3) using the N fund returns in period t, which form the basis for the FM method. The pseudo true value[1] for the OLS estimator $\hat{\gamma}_{1t}$ is given by

$$\gamma^*_{1t} = \frac{\mathrm{Cov}_t[r_{it}, r_{i,t-1}]}{\mathrm{V}_t[r_{i,t-1}]}, \tag{7}$$

where the suffix t attached to the (co)variances is used to indicate *cross-sectional* (co)variances[2] for all funds that are available at time t. Note that in a cross-section at time t, the market returns in period t or before can be considered as given. Using the data generating process in (6), it can be shown that

$$\mathrm{Cov}_t[r_{it}, r_{i,t-1}] = \sigma^2_\beta r_{mt} r_{m,t-1}, \tag{8}$$

which can be either positive or negative, and that

$$\mathrm{V}_t[r_{i,t-1}] = \sigma^2_\beta r^2_{mt} + V_t[\eta_{it}]. \tag{9}$$

The result in (8) shows that the problem of cross-sectional correlation between r_{it} and $r_{i,t-1}$, even when r_{mt} and u_{it} are serially uncorrelated, is due to cross-sectional variation in expected returns over the funds. The *FM* estimate, obtained as the time-average of $\hat{\gamma}_{1t}$, also suffers from a non-zero pseudo true value (and thus a bias) as the average of (8) nor the average ratio of (8) and (9) is equal to zero. The bias in the *FM* estimator can be expected to be positive, as r_{mt}, though uncorrelated over time, will have a positive mean.

In order to eliminate the above bias, Jegadeesh [1990] suggests to adjust the lefthand side of (3) by subtracting an unbiased estimate for the expected return[3], based on a moving average of S future returns. Alternatively, the sample average return, or the predicted value from the one-factor model can be used. This results in the methods referred to as *FM1*, *FM2* and *FM3*, respectively. The pseudo true value of the resulting estimators can be obtained by replacing the numerator in (7) by $Cov_t[r_{it} - M_{t-1}(r_{it}), r_{i,t-1}]$, with the appropriate choice for $M_{t-1}(r_{it})$. Ideally, $M_{t-1}(r_{it})$ is correlated with $r_{i,t-1}$ in such a way that the numerator in (7) equals zero (on average).

Let us now consider the pseudo true value of the OLS estimator for γ_{1t} in these three cases. Using the assumptions of the data generating process in (6), the following expression for the numerator can be derived for the *FM1* method

$$Cov_t[r_{it} - M_{t-1}(r_{it}), r_{i,t-1}] = \sigma^2_\beta (r_{mt} - \bar{r}^*_{m,t}) r_{m,t-1} \tag{10}$$

[1]The pseudo true value of an estimator $\hat{\theta}_N$ is defined as the probability limit of that estimator when $N \to \infty$.

[2]Note that this is not the same as conditional (co)variances.

[3]Due to a slightly different assumption on the data generating process, the expressions in Jagadeesh are similar but not identical to ours.

where $\bar{r}^*_{m,t}$ denotes the average market return over the period $t+1$ to $t+S$ ($S > 0$). Taking the expectation over t in this numerator gives zero, where we use the assumption that r_{mt} are independent drawings from a distribution with a constant mean μ_m and variance σ^2_m. Consequently, we do not expect a bias for this estimator.

However, in the *FM2* procedure, where the average return over the whole sample period is employed, we have

$$Cov_t[r_{it} - M_{t-1}(r_{it}), r_{i,t-1}] = \sigma^2_\beta (r_{mt} - \bar{r}_m) r_{m,t-1} + \frac{1}{T} V_t[\eta_{it}] \tag{11}$$

which differs in two aspects from (10). First, the presence of an additional second term and second, the average market return $\bar{r}_m$ now also includes $r_{m,t-1}$. Consequently, taking the expectation over t in (11) gives a non-zero value. Furthermore, combining (11) with (9) and taking expectations over t in numerator and denominator, results in the following expression for the pseudo true value of the *FM2* estimator[4]

$$\gamma^*_1 \approx -\frac{1}{T} \frac{\sigma^2_\beta \sigma^2_m + V[\eta_{it}]}{\sigma^2_\beta(\sigma^2_m + \mu^2_m) + V[\eta_{it}]}, \tag{12}$$

which implies that the expected bias is negative and in absolute value somewhat less than $\frac{1}{T}$.[5]

Considering the data generating process (6), the *FM3* procedure is now based on the returns predicted by the linear one-factor model, i.e. $M_{t-1}(r_{it})$ is based on a time series regression of r_{it} on r_{mt}. Using the expression for the OLS estimators for the intercept term, one can write

$$M_{t-1}(r_{it}) = \bar{r}_i + \hat{\tau}_{1i}(r_{mt} - \bar{r}_m), \tag{13}$$

where

$$\hat{\tau}_{1i} = \frac{\sum_t (r_{it} - \bar{r}_i)(r_{mt} - \bar{r}_m)}{\sum_t (r_{mt} - \bar{r}_m)^2}. \tag{14}$$

From this, it follows that

$$\text{Cov}_t[M_{t-1}(r_{it}), r_{i,t-1}] = \sigma^2_\beta r_{mt} r_{m,t-1} + T^{-1} \text{V}_t[\eta_{it}], \tag{15}$$

[4]The approximation sign is due to the fact that we do not take expectations over the ratio but over numerator and denominator separately.

[5]Hendricks, Patel and Zeckhauser [1993] seem to encounter a bias of this magnitude in their bootstrap simulations discussed at the end of the paper (compare their footnote 22). They do not, however, adjust their claim that "the estimated slope coefficients are unbiased" (their Table 1).

Combining this result with (8) gives

$$\text{Cov}_t[r_{it} - M_{t-1}(r_{it}), r_{i,t-1}] = -T^{-1}V_t[\eta_{it}]. \tag{16}$$

Consequently, we can expect a slightly smaller bias (in absolute value) in the *FM3* estimator based on predicted returns from the factor model compared to the one based on average historical returns. The comparable expression to (12) is given by

$$\gamma_1^* \approx -\frac{1}{T}\frac{V[\eta_{it}]}{\sigma_\beta^2(\sigma_m^2 + \mu_m^2) + V[\eta_{it}]}. \tag{17}$$

Finally, let us consider the *pooled IV* method. The pseudo true value of the IV estimator for γ_1 is now equal to

$$\gamma_1^* = \frac{\text{Cov}[(r_{it}^* - r_{it-1}^*), r_{it-2}]}{\text{Cov}[(r_{it-1}^* - r_{it-2}^*), r_{it-2}]} \tag{18}$$

where the covariances now denote covariance over all N funds and T time periods, and the starred returns denote returns in excess of the average return over all funds in the same period.[6] Considering the assumptions of the data generating process (6), the numerator in (18) equals

$$\text{Cov}[(r_{it}^* - r_{it-1}^*), r_{it-2}] = \sigma_\beta^2 \text{E}[(r_{mt}^* - r_{mt-1}^*)\, r_{mt-2}] = 0. \tag{19}$$

Thus, similar to the *FM1* method, we can expect a zero bias for this *pooled IV* estimator.

Recall that the five methods discussed above are used to estimate the predictable behavior in mutual fund returns. All methods give an estimate of the average persistence coefficient for the first lag. However, under our data generating process, any superior performance is due to luck, and is not an indication for future performance. Nevertheless, some of the methods discussed above do find a spurious pattern of persistence in returns. The size and sign of this asymptotic bias for the five estimation methods are summarized in Table 1. In case of the standard *FM* approach, the size of the bias depends heavily upon the data generating process. In contrast, the bias in the adjusted Fama Macbeth methods *FM2* and *FM3* is hardly influenced by the true data generating process, but depends heavily on the number of periods, T, used to construct the average return $\bar{r}_i$. For simplicity, we have assumed that T is the same for all funds, but in reality the sample of funds is

[6] Transforming all variables like this is equivalent to including a time dummy for each period.

Table 1: Asymptotic bias in γ_1-estimates

Estimation Method	Expected Size and Sign
FM	Bias > 0
FM1	Bias $= 0$
FM2	Bias $\approx -\frac{1}{T}$
FM3	$-\frac{1}{T} <$ Bias < 0
Pooled IV	Bias ≈ 0

Overview of the expected sign and size of the asymptotic bias in the estimated first persistence coefficients, where T is the number of time series observations available per fund.

typically unbalanced with an increasingly small number of observations for earlier periods. In that case, the absolute bias in the *FM2* method is some weighted average of $\frac{1}{T_i}$, T_i being the number of periods available for fund i, which may be substantially larger than $\frac{1}{T}$, where T denotes the maximum number of sample periods. We shall illustrate this in the simulation exercise in the next section.

It is clear from all expressions above that the biases disappear if T tends to infinity, except for the standard *FM* method. With increasing T, the correlation between the estimation error in $M_{t-1}(r_{it})$ and any historical return (i.e. $r_{i,t-1}$) tends to zero. In practice, however, only a finite history is available for each fund in the sample such that the bias may not be negligible, particularly given the order of magnitude of persistence coefficients found in the literature. Moreover, as under the null hypothesis of no predictability in returns, the returns are uncorrelated over time, the bias is similar for all coefficients if additional lags are included in the regression ($J > 1$). So the cumulative bias in a regression with 8 lags included is of the order $8/T$. This will be one of the points we will illustrate in the simulation exercise in the next section.

4 Properties of the Estimators: Numerical Results

To simplify the analytical derivations, we assumed that there was only one lag ($J = 1$) included in the regressions. To illustrate the numerical magnitude of the biases in some of the estimation methods when more than one lag is included, we performed a number of Monte Carlo simulation experiments. For the first experiment, we assume that true fund returns can be described by a one factor model with an unpredictable factor. This corresponds to a null hypothesis of no predictability in returns. In a second experiment, we examine the behavior of the five estimation methods when true funds returns do have a predictable component.

For the first experiment, we generate returns for a sample of 750 mutual funds over 60 periods. To do this, we follow the set-up of Brown, Goetzmann, Ibbotson and Ross [1992], whose parameter values were based on Ibbotson and Sinquefeld [1990], while increasing the frequency to quarterly observations. Quarterly returns are generated from the one factor model

$$r_{it} = \beta_i(R_{mt} - r_f) + u_{it}, \tag{20}$$

where the quarterly risk free rate r_f is taken to be 0.0175 (corresponding to an annual rate of 7 %) and the quarterly risk premium $R_{mt} - r_f$ is assumed to be normal with mean 0.022 and standard deviation 0.104. The idiosyncratic error term u_{it} is independent of the risk premium $R_{mt} - r_f$, and also assumed to be normal with mean zero and variance σ_i^2, given by

$$\sigma_i^2 = k(1 - \beta_i)^2. \tag{21}$$

This relationship is a rough approximation to the relationship between non-systematic risk and β that is often observed in mutual funds data. The value of k in our experiment equals 0.01337. Finally, the distribution of fund betas is assumed to be normal with mean 0.95 and a standard deviation of 0.25.

In the Monte Carlo experiment we generate 2500 samples with 750 funds observed over 60 consecutive quarters. Following Hendricks, Patel and Zeckhauser [1993], we now include eight lags in the regressions ($J = 8$). For the standard *FM* estimation method and the adjusted *FM2* and *FM3* methods, we estimate, for each sample, 52 cross-sectional regressions and computed the average coefficient estimates. For the adjusted *FM1* method only 44 cross-sectional regressions are performed. The *pooled IV* estimation method implies that only one regression has to be estimated for each sample. The numbers reported correspond to the average estimates of the 2500 replications and the average t-values.

For the first method, *FM*, we can expect a (small) bias due to the cross-sectional variation in expected returns. The second method, *FM1*, replicates Jegadeesh's solution by subtracting the average return over the eight quarters following[7] quarter t, which should yield unbiased estimates. The next two choices correspond to *FM2* and *FM3* and subtract the average return over

[7] Due to this choice, for the last eight quarters of data no cross-sectional regression can be performed; the estimates presented are averages over 44 quarters.

the whole sample period and the predicted return from a CAPM time-series regression, respectively. Both methods are expected to yield a negative bias. The final method, *pooled IV*, is based on instrumental variables estimation of a pooled regression in terms of first differences of returns, and should yield unbiased results.

The results are summarized in Table 2. Clearly, the magnitude of the biases found corresponds closely to the analytical expressions given above. For the standard *FM* method, a small positive bias is found of approximately 0.004 in all slope coefficients, while for Jegadeesh's solution biases are negligible[8]. For adjusted Fama-MacBeth procedures *FM2* and *FM3*, corresponding to the Hendricks, Patel and Zeckhauser [1993] choices, a negative bias is found in all slope coefficient estimates of the order of -0.016 and -0.014, respectively. Note that in the *FM3* approach, the market model used to estimate M_{t-1} corresponds to the true data generating process and will probably result in a better fit than commonly found in applied work. Although the negative numbers found seem small, the bias is shared by all coefficients such that the cumulative of all eight coefficients is biased by about -0.13. Interpreting this along the lines of Hendricks, Patel and Zeckhauser [1993], this implies that in the wake of a 1% superior performance, the cumulative residual loss is about 13 basis points over the next eight quarters[9]. Moreover, increasing the number of lags in the regression, would result in even more coefficients that are biased in the same direction. The *pooled IV* method gives coefficients that vary between -0.003 and +0.004 with rather high standard errors.

The average t-values reported in the table, except those for the *pooled IV* method, are based on the usual Fama-Macbeth standard errors and are thus adjusted for heteroskedasticity over time and over the funds. Compared to the other alternative Fama Macbeth approaches, the standard errors for the case with residual returns from the market model (*FM3*) are small. This is probably due to the fact that the variation over time in residual returns $(r_{it} - \hat{r}_{it})$ is much smaller than the variation in excess returns $(r_{it} - \bar{r}_i)$. Also note that the market model used in this approach is correctly specified by construction. While this will hardly affect the average coefficient estimates, it will reduce their variation over time. For the *pooled IV* method, t-values are calculated assuming homoskedasticity across time (but not across funds) and allowing for first order (moving average) autocorrelation in the differenced errors. The standard errors are substantially higher than for the other approaches. Apparently, robustness pays a price in terms of efficiency.

While for the adjusted *FM2* and *FM3* methods none of the slope co-

[8]That is, insignificantly different from zero, using the Monte Carlo standard errors

[9]HPZ report a cumulative residual gain of 20 basis points over 8 quarters.

Table 2: Average estimates and t-values; simulated data without persistence (2500 replications)

Average estimates (x 100), t-values in parentheses					
Estimation method	Standard FM	Adjusted FM1	Adjusted FM2	Adjusted FM3	Pooled IV
Dependent variable	r_{it}	$r_{it} - \bar{r}_i^*$	$r_{it} - \bar{r}_i$	$r_{it} - \hat{M}_{t-1}$	$r_{it}^* - r_{it-1}^*$
$\bar{\gamma}_1$	0.41	-0.00	-1.63	-1.45	0.39
	(0.23)	(-0.00)	(-0.95)	(-1.80)	(0.04)
$\bar{\gamma}_2$	0.50	0.06	-1.55	-1.46	-0.18
	(0.27)	(0.03)	(-0.91)	(-1.82)	(-0.02)
$\bar{\gamma}_3$	0.46	0.00	-1.59	-1.44	0.25
	(0.25)	(0.01)	(0.92)	(-1.81)	(0.03)
$\bar{\gamma}_4$	0.40	-0.06	-1.65	-1.46	0.08
	(0.22)	(-0.03)	(-0.95)	(-1.82)	(0.01)
$\bar{\gamma}_5$	0.43	-0.02	-1.62	-1.43	-0.16
	(0.24)	(-0.00)	(-0.94)	(-1.79)	(-0.00)
$\bar{\gamma}_6$	0.45	-0.00	-1.60	-1.43	-0.22
	(0.26)	(0.00)	(-0.93)	(-1.79)	(-0.04)
$\bar{\gamma}_7$	0.41	-0.04	-1.64	-1.45	0.17
	(0.23)	(-0.02)	(-0.95)	(-1.81)	(0.00)
$\bar{\gamma}_8$	0.51	0.09	-1.54	-1.42	-0.26
	(0.28)	(0.05)	(-0.89)	(-1.79)	(-0.04)
$\sum \bar{\gamma}_j$	3.57	0.03	-12.82	-12.97	0.07
	(0.51)	(0.09)	(-2.59)	(-5.08)	(0.09)

For the Fama Macbeth methods, cross-sectional regressions are estimated by OLS, for each period (t=9,..,60). The estimates reported are the time-averages of the slope coefficient estimates. For the methods adjusted Fama Macbeth 1,2 and 3, the dependent variable is in excess of an estimate of the expected return. All numbers are averages over 2500 Monte Carlo replications. In each period, the full sample of 750 funds is available.

efficients is individually significantly different from zero (according to the average t-values), a joint test leads to rejection. Moreover, the cumulative residual gain, as measured by the estimates of $\sum_j \gamma_j$, is significantly different from zero for each of the biased methods *FM2* and *FM3*.

It is clear that the estimation error in estimating "equilibrium" returns induces a bias in the slope coefficient estimates, which in itself may be small, but may seriously affect economic conclusions. The biases are all negative, implying that it cannot induce spurious findings of "hot hands" in mutual funds. It may, however, indicate that the "hot hands" phenomenon is even stronger than reported by Hendricks, Patel and Zeckhauser [1993].

The set-up of the second experiment is comparable with the first one. However, quarterly returns are now generated by

$$r_{it} = \beta_i(R_{mt} - r_f) + \gamma_1 r_{i,t-1} + u_{it}, \tag{22}$$

with $\gamma_1 = 0.05$, while the other parameter values are left unchanged.[10] Essentially, the data generating process (22) includes a simple predictable pattern of past returns. Ideally, the estimation methods should yield a positive (and significant) coefficient for the first lag and zero values for the others. The results of 2500 Monte Carlo simulations are summarized in Table 3.

The order of the biases, present in the five estimation methods, in the case that the true data generating process contains a predictable component are comparable to those found with the unpredictable process. The *FM2* and *FM3* methods seriously underestimate the true coefficients. Jegadeesh's approach, *FM1*, produces estimates close to the coefficient $\gamma_1 = 0.05$, but as mentioned before, has the disadvantage that future returns are required. Despite the fact that it uses a longer sample period, the standard errors of the *pooled IV* approach are approximately five times as large as those of the *FM1* method, which seems to make the IV approach inappropriate for applied work.

Until now, our sample of mutual funds was not very representative for samples used in empirical work, as it is assumed that fund returns are available over the whole sample period of 60 quarters. To see how the conclusions are affected if funds returns are observed over a limited history only, we took our previous sample of the first experiment and, going back in time, *randomly* removed 2% of the funds in each quarter. This results in an average number of funds in the first quarter of 223 (30%), which seems reasonable given the growth in the number of U.S. mutual funds over the last decade. It is important to realize two things. First, it is not the number of funds that is relevant for the biases, but the (average) number of periods used to

[10] Note that this increases the overall average excess return by about 5%.

Table 3: Average estimates and t-values; simulated data with first order persistence (2500 replications)

Average estimates (x 100), t-values in parentheses					
Estimation method	Standard FM	Adjusted FM1	Adjusted FM2	Adjusted FM3	Pooled IV
Dependent variable	r_{it}	$r_{it} - \bar{r}_i^*$	$r_{it} - \bar{r}_i$	$r_{it} - \hat{M}_{t-1}$	$r_{it}^* - r_{it-1}^*$
$\bar{\gamma}_1$	5.51	5.03	3.36	3.38	5.25
	(3.12)	(2.53)	(1.95)	(4.21)	(0.48)
$\bar{\gamma}_2$	0.40	-0.04	-1.64	-1.48	-0.22
	(0.23)	(-0.02)	(-0.95)	(-1.84)	(-0.02)
$\bar{\gamma}_3$	0.49	0.09	-1.55)	-1.44	0.01
	(0.28)	(0.04)	(-0.90	(-1.79)	(0.00)
$\bar{\gamma}_4$	0.36	-0.07	-1.67	-1.49	-0.26
	(0.20)	(-0.03)	(-0.96)	(-1.85)	(-0.02)
$\bar{\gamma}_5$	0.40	-0.01	-1.63	-1.47	0.40
	(0.23)	(-0.00)	(-0.95)	(-1.83)	(0.03)
$\bar{\gamma}_6$	0.42	0.01	-1.62	-1.46	-0.32
	(0.24)	(0.01)	(-0.94)	(-1.83)	(-0.04)
$\bar{\gamma}_7$	0.37	-0.09	-1.67	-1.48	0.15
	(0.20)	(-0.04)	(-0.97)	(-1.85)	(0.00)
$\bar{\gamma}_8$	0.41	-0.04	-1.74	-1.55	-0.29
	(0.23)	(-0.02)	(-1.00)	(-1.93)	(-0.04)
$\sum \bar{\gamma}_j$	8.36	4.88	-8.16	-6.99	4.72
	(1.55)	(0.87)	(-1.71)	(-3.25)	(0.07)

For the Fama Macbeth methods, cross-sectional regressions are estimated by OLS, for each period (t=9,..,60). The estimates reported are the time-averages of the slope coefficient estimates. For the methods adjusted Fama Macbeth 1,2 and 3, the dependent variable is in excess of an estimate of the expected return. All numbers are averages over 2500 Monte Carlo replications. In each period, the full sample of 750 funds is available.

estimate M_{t-1}. Using the 223 funds existing over the whole sample period would produce biases similar to those reported in Table 2. Second, there is no survivorship bias here, as the disappearing funds are selected completely randomly. Any survivorship bias would come above the estimation bias discussed here (although the two biases can have opposite sign and may cancel out).

The results for the selected sample are presented in Table 4. As expected, the biases increase in absolute size compared to those reported in Table 2, except for the standard *FM* approach, the adjusted *FM1* approach and the *pooled IV* method.

Finally, we checked how sensitive the reported biases were for the particular parameter values chosen. As expected, varying the parameter values within reasonable bounds hardly had an effect on the numbers in the Tables 2, 3 and 4, except for the standard *FM* estimator. The t-values appeared less insensitive to the parameter values; in particular a smaller variance of the market risk premium led to an increase of the t-values for all estimators, except for the *FM3* approach. Substantial changes, however, were encountered when the number of periods was reduced to 30, in which case the biases almost doubled. It is important to keep this in mind as an analysis based on yearly data would produce similar results if the number of years employed in estimating M_{t-1} is the same as the number of quarters used in this study. Clearly, 60 years of data are available for only very few mutual funds, so that with annual data the biases encountered may be much larger than those reported here.

5 Empirical results for 1986-1994

Several recent empirical studies report short-run persistence in mutual fund performance. In light of our results of the previous two sections, we shall, in this section, empirically examine whether mutual funds do have a pattern of predictable returns using a sample of U.S. open-end mutual funds over the period 1986-1994. This analysis will illustrate the order of magnitudes of persistence coefficients that are relevant for applied work, so as to clarify the importance of the, seemingly small, biases reported in the previous sections.

Hendricks, Patel and Zeckhauser [1993], looking at short-run persistence of mutual fund returns over the period 1974-1988, found a pattern of positive coefficients for the first four lagged quarterly returns, while lags 5 to 7 were negative, and lag 8 was positive again. The cumulative gain in expected returns by selecting the funds that have an above average return is, according to their estimates, about 30 basis points over the next four quarters, but

Table 4: Average estimates and t-values; selected sample from simulated data (2500 replications)

Average estimates (x 100), t-values in parentheses					
Estimation method	Standard FM	Adjusted FM1	Adjusted FM2	Adjusted FM3	Pooled IV
Dependent variable	r_{it}	$r_{it} - \bar{r}_i^*$	$r_{it} - \bar{r}_i$	$r_{it} - \hat{M}_{t-1}$	$r_{it}^* - r_{it-1}^*$
$\bar{\gamma}_1$	0.37	-0.10	-2.08	-1.80	0.21
	(0.18)	(-0.05)	(-1.07)	(-1.57)	(0.07)
$\bar{\gamma}_2$	0.45	-0.00	-2.00	-1.78	-0.16
	(0.23)	(-0.00)	(-1.03)	(-1.55)	(-0.06)
$\bar{\gamma}_3$	0.51	0.06	-1.94	-1.78	0.23
	(0.26)	(0.03)	(-1.00)	(-1.55)	(0.06)
$\bar{\gamma}_4$	0.44	-0.03	-2.01	-1.79	-0.34
	(0.22)	(-0.01)	(-1.04)	(-1.56)	(-0.05)
$\bar{\gamma}_5$	0.48	0.03	-1.97	-1.76	0.30
	(0.24)	(0.01)	(-1.02)	(-1.54)	(0.05)
$\bar{\gamma}_6$	0.45	-0.02	-2.00	-1.83	0.02
	(0.22)	(-0.01)	(-1.03)	(-1.59)	(0.03)
$\bar{\gamma}_7$	0.42	-0.06	-2.03	-1.79	0.25
	(0.20)	(-0.03)	(-1.05)	(-1.57)	(0.04)
$\bar{\gamma}_8$	0.42	-0.05	-2.03	-1.80	-0.07
	(0.21)	(-0.02)	(-1.04)	(-1.57)	(-0.05)
$\sum \bar{\gamma}_j$	3.54	-0.17	-16.06	-14.33	0.44
	(0.52)	(-0.06)	(-2.83)	(-4.39)	(0.09)

For the Fama Macbeth methods, cross-sectional regressions are estimated by OLS, for each period (t=9,..,60). The estimates reported are the time-averages of the slope coefficient estimates. For the methods adjusted Fama Macbeth 1,2 and 3, the dependent variable is in excess of an estimate of the expected return. All numbers are averages over 2500 Monte Carlo replications. In each period, a random 2% of new funds are added to the sample, such that in the last period 750 mutual funds exist.

declines to about 20 basis points after eight quarters.

To examine whether a similar pattern of persistence is present over the period 1986-1994, we employ two samples of quarterly mutual fund returns over the period 1986 to 1994. The mutual funds data are obtained from the Morningstar Mutual Fund Database. Morningstar reports information about all open-end mutual funds on a monthly basis. Following Hendricks, Patel and Zeckhauser [1993], we attempt to minimize the effect of survivorship in our samples by including the fund returns until the moment of disappearance. Most of these disappearing funds merged with another fund, became a closed-end fund or simply ceased to exist. The basic sample includes funds that meet the following selection criteria. First, the fund has an observation record of at least nine quarters[11]. Second, funds that invest more than 50 % in bonds, but nevertheless advertise as "equity fund" are excluded from the sample. As a consequence of our first criterium, funds that ceased to exist before January 1988 are also excluded from the sample. The resulting sample varies from 711 mutual funds in the first quarter of 1986 to 1422 funds in the fourth quarter of 1994.

Following several papers in the area, our second sample contains a relatively homogeneous sample of equity funds, selected out of the basic sample, with as investment objective growth stocks. The size of this sample varies between 171 funds in the first quarter of 1986 and 353 mutual funds in the fourth quarter of 1994. For both samples we assume that all dividends are reinvested in the mutual fund at the end of the quarter in which the dividends are distributed. For the riskless rate we take the quarterly return on one-month U.S. Treasury bills, collected from the Ibbotson Index database. In order to apply the *FM3* method, we use the Standard & Poor 500 index, also collected from the Ibbotson Index database, as the market return. All returns are net of transaction costs, fees, and expenses, but are gross for any sales charges.

Although the choice of the number of lags in the regressions is a bit arbitrary, we follow Hendricks, Patel and Zeckhauser [1993], and only include up to eight lags, as in our simulation experiments. Including more lags would enable estimation of additional medium-run persistence effects, but effectively reduces the number of observations in estimation. The estimation results of the five methods are summarized in Table 5, for the basic sample, and Table 6 for the sample of growth stocks.

As discussed above, the *FM2* method has an expected bias that is a

[11]To apply *FM2*, we also need eight future observations, so that for this approach an observation history of at least 17 periods is required. This leads to a sample of 1209 funds (284 growth funds) in the last quarter of 1992.

Table 5: Persistence estimates and t-values: basic sample 1986-1994

Estimates (x 100) of Persistence Coefficients					
t-values in parentheses					
Estimation method	Standard FM	Adjusted FM1	Adjusted FM2	Adjusted FM3	Pooled IV
Dependent variable	r_{it}	$r_{it} - \bar{r}_i^*$	$r_{it} - \bar{r}_i$	$r_{it} - \hat{M}_{t-1}$	$r_{it}^* - r_{it-1}^*$
$\bar{\gamma}_1$	1.60	-3.86	-3.67	-1.94	4.54
	(0.32)	(-0.64)	(-0.75)	(-0.48)	(0.62)
$\bar{\gamma}_2$	1.16	-3.18	-3.42	-0.78	-0.31
	(0.26)	(-0.67)	(-0.80)	(-0.21)	(-0.39)
$\bar{\gamma}_3$	17.43	19.57	12.81	9.79	33.43
	(4.25)	(3.49)	(3.26)	(3.03)	(4.18)
$\bar{\gamma}_4$	0.11	4.90	-3.59	-1.98	3.65
	(0.03)	(0.98)	(-0.96)	(-0.58)	(0.58)
$\bar{\gamma}_5$	-7.39	-6.18	-11.03	-10.32	-0.42
	(-1.70)	(-1.40)	(-2.52)	(-2.21)	(-0.07)
$\bar{\gamma}_6$	-1.08	0.01	-5.49	-4.48	0.23
	(-0.38)	(0.00)	(-1.93)	(-1.51)	(0.03)
$\bar{\gamma}_7$	0.49	-4.96	-4.21	-4.13	12.87
	(0.15)	(-1.60)	(-1.33)	(-1.25)	(1.65)
$\bar{\gamma}_8$	12.63	9.20	7.98	3.22	17.72
	(4.19)	(2.26)	(2.56)	(1.15)	(2.51)
$\sum \bar{\gamma}_j$	24.94	15.40	-10.60	-10.62	71.71
	(3.03)	(1.60)	(-1.48)	(-1.48)	(1.58)

The estimates of the adjusted FM1 method are based on cross-sectional regressions, estimated by OLS, for each quarter in 1988 through 1992 (t=9,..,28). In contrast, the standard FM and adjusted FM2 and FM3 approaches are based on 28 cross-sectional regressions. The estimates reported are the time-averages of the slope coefficient estimates. For the methods adjusted FM 1,2 and 3, the dependent variable is in excess of an estimate of the expected return.

Table 6: Persistence estimates and t-values for selected sample of growth funds

Estimates (x 100) of Persistence Coefficients,					
t-values in parentheses					
Estimation method	Standard FM	Adjusted FM1	Adjusted FM2	Adjusted FM3	Pooled IV
Dependent variable	r_{it}	$r_{it} - \bar{r}_i^*$	$r_{it} - \bar{r}_i$	$r_{it} - \hat{M}_{t-1}$	$r_{it}^* - r_{it-1}^*$
$\bar{\gamma}_1$	4.05	0.03	-0.84	-0.76	2.18
	(0.72)	(0.00)	(-0.15)	(-0.16)	(0.27)
$\bar{\gamma}_2$	5.62	1.68	1.61	3.83	4.82
	(1.11)	(0.27)	(0.32)	(0.84)	(0.54)
$\bar{\gamma}_3$	12.93	11.62	8.92	6.56	43.65
	(2.40)	(1.62)	(1.73)	(1.49)	(4.77)
$\bar{\gamma}_4$	3.10	6.27	-4.88	-0.31	2.86
	(0.79)	(1.40)	(-0.13)	(-0.08)	(0.42)
$\bar{\gamma}_5$	-8.03	-2.34	-11.08	-10.89	2.53
	(-1.52)	(-0.50)	(-2.10)	(-1.96)	(0.36)
$\bar{\gamma}_6$	-2.80	0.82	-3.63	-3.22	-3.34
	(-0.08)	(0.19)	(-1.12)	(-0.93)	(-0.44)
$\bar{\gamma}_7$	-1.81	-3.65	-5.26	-5.46	19.86
	(-0.55)	(-1.07)	(-1.61)	(-1.58)	(2.10)
$\bar{\gamma}_8$	8.84	8.73	5.20	1.95	17.79
	(3.17)	(2.11)	(1.67)	(0.73)	(2.11)
$\sum \bar{\gamma}_j$	21.90	23.20	-9.90	-8.30	90.53
	(2.24)	(1.79)	(-0.52)	(-0.75)	(1.81)

The estimates of the adjusted FM1 method are based on cross-sectional regressions, estimated by OLS, for each quarter in 1988 through 1992 (t=9,..,28). In contrast, the standard FM and adjusted FM2 and FM3 approaches are based on 28 cross-sectional regressions. The estimates reported are the time-averages of the slope coefficient estimates. For the methods adjusted FM 1,2 and 3, the dependent variable is in excess of an estimate of the expected return.

weighted average of $-\frac{1}{T_i}$, where T_i is the number of periods available for fund i. In this empirical study, the maximum number of observations available is 36, which means that we can expect a bias of at least -0.028 in the estimated coefficients of this method. According to our simulation experiments, the bias in the estimates of the *FM1* method is negligible. Note, however, that in our case the estimates are the averages of only 20 cross-sectional regressions due to the fact that the unconditional expectation M_{t-1} is estimated from eight future observations. In contrast, the standard *FM* estimates are based on 28 cross-sectional regressions. Although the exact size of the bias present in the latter estimation method is dependent on the true data generating process, we expect a positive sign. This suggests that the true persistence coefficients are somewhat smaller than the estimates of the standard Fama Macbeth approach. The estimates of the *pooled IV* approach differ substantially from the estimates of the standard *FM* and *FM1* method. As already suggested, the *pooled IV* method suffers from large standard errors, which makes this approach less suitable for applied work.

Looking at the estimates of the adjusted *FM1* method, there appears to be some evidence of persistence in the basic sample of mutual funds, but the pattern is rather erratic. Given the accuracy of the individual estimates, it does not seem advisable to develop a dynamic buy-and-sell strategy from these numbers. A strategy that selects funds with a 1 % superior performance, and keeps these in portfolio for eight consecutive quarters, leads to a expected cumulative residual gain of 0.15 %, with a standard error of 0.10 %. The conclusions from the inconsistent *FM2* and *FM3* methods, on the other hand, would be substantially different with a cumulative residual *loss* of 0.10% and a standard error of 0.07 %. The estimates using the standard *FM* approach, reported in the first column, seems to be upward biased, as can be expected from the analytical and Monte Carlo results, while the *pooled IV* estimates in column 5 produces substantially different results, with substantially higher standard errors. Most methods seem to have in common that lags 3 and 8 are important with significantly positive coefficients.

For the more homogenous subsample of growth funds, our *FM1* results, reported in column 2 of Table 6, show a pattern of persistence that corresponds fairly closely to the one reported by Hendricks, Patel and Zeckhauser [1993] for the period 1974 to 1988. Note, however, that the latter results were based on the adjusted methods *FM2* and *FM3*, which - in our case - would yield substantially different outcomes. Apparently, an investment strategy based on selecting growth-oriented mutual funds with an above average performance over the last four quarters still proves valuable for the period 1986-1994. The estimated cumulative gain in expected returns by selecting funds with a relatively high return compared to other growth funds is about 23 basis points over the next eight quarters. The associated standard error, however, corresponds to 13 basis points. Again, note that the conclusions from the adjusted *FM2* and *FM3* approaches would be substantially different with a cumulative loss of approximately 9 basis points. Recall that this is a biased estimate and does not represent the actual expected gain or loss from the above-mentioned strategy.

6 Concluding remarks

In this paper we examined a number of estimation methods used to detect patterns of predictable returns. As expected returns vary over the funds, most of these methods employ some estimate of these expected returns to prevent the problem of cross-sectional correlation, as discussed by Jegadeesh [1990]. Our analytical results show that estimation errors in the expected returns may induce a spurious pattern of short-run persistence. The bias in the persistence coefficients is, on average, close to $-\frac{1}{T}$, where T is the number of periods used to estimate the expected returns. As this bias hardly depends on the true data generating process, this result is of particular concern when using lower frequency data, where only a limited number of time series observations is available. As an illustration, we considered the approaches taken in Hendricks, Patel and Zeckhauser [1993], which had biases in each slope coefficient of approximately -0.02, corresponding to a cumulative bias (over eight lags) of -0.16.

Jegadeesh's [1990] approach to eliminate such biases requires estimation of expected returns over future observations, instead of past returns. Although this methods leads to unbiased estimates, the approach has as a disadvantage that the most recent observation periods are actually not used in the estimation of the short-run persistence coefficients. This is particularly cumbersome if time-variation in these coefficients can be expected. As an alternative, we suggest another estimation approach, which corresponds to instrumental variables estimation of the model in first differences, using the pooled data. Unfortunately, this approach, based on the elimination of fixed individual effects in dynamic panel data models, is, though consistent, rather inefficient, such that accurate statements about the true persistence coefficients are hard to make.

The second part of the paper empirically examined the short-run persistence in a sample of equity funds and a subsample of growth equity funds, over the period 1986-1994. The results show that an investment strategy based on identifying the winning growth-oriented mutual funds increases the expected return on a portfolio of mutual funds. In particular, a strategy of selecting every quarter the funds with high returns, relative to other funds, over the last four quarters, can significantly increase the expected return. Although the estimates of Hendricks, Patel and Zeckhauser [1993] over the period 1975 to 1988 were negatively biased, they found a similar pattern. Apparently, the hot hands phenomenon reported by these authors still exists in the period 1986 to 1994. It must be stressed, however, that the estimates of the individual coefficients are not very accurate and, moreover, the results are quite sensitive to the estimation method employed. At the least, this implies that the development of dynamic trading strategies from these results is a dangerous exercise.

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