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THE EFFECTS OF DATA-SNOOPING BIAS ON MUTUAL FUND PERFORMANCE

Introduction

The performance of mutual funds has been one of the main issues in the financial academia and in the financial industry. The investment decisions are often made by comparing the main fund performance evaluation measures such as raw returns, Sharpe ratios or the intercepts, obtained from factors models, to the benchmark performance measures. The crucial question is whether statistical inferences made from large-scale number of methods are correct. Often, due to the limitations in the financial data sets, in fact there are only few available financial data sets, researchers are facing different obstacles when conducting empirical analysis. Lo and MacKinlay (1990) and Brock, Lakonishok, and LeBaron (1992) were one of the first to document the data-snooping bias in financial studies[1,2]. Lo and MacKinlay write: "The reliance of economic science upon non-experimental inference is, at once, one of the most challenging and most nettlesome aspects of the discipline"[3]. The constant reuse of the same financial data by the researchers leads to the data-snooping or data mining[4]. As same data set is tested for different models and assets, individual statistics generated from the same data set are related to each other, yielding misleading inferences.

In the context of evaluating mutual fund performance, the re-examination of different models and different performance measures using the same data set, might end up with some funds showing superior managerial abilities, yet such superior performance may simply be an outcome of luck.

This paper quantifies possible data-snooping biases for the actively managed equity mutual funds and tests whether the performance of these funds is truly superior relative to given benchmarks, such as S&P 500. For this purpose, we use powerful testing methods, specifically, White's (2000)'s "Reality Check" and its stepwise extension by Romano and Wolf (2005) the "Step-RC"[56].

The results of our tests suggest that, when data snooping-bias is not considered, the performance of mutual funds under given performance criterion might be highly statistically significant relative to their benchmarks. However, once we control for the effects of data-snooping, the number of outperforming mutual funds decreases dramatically. The results are robust relative to all included benchmarks. The inference made from the results is that the performance of most of the funds is simply due to luck and only few funds possess real superior ability to outperform the market indices.

Data

We use daily data from CRSP Survivor-Bias-Free U.S. Mutual Fund database to build the sample of actively managed U.S. equity funds. As we are interested only in actively managed equity mutual funds we drop any funds that is identified as index funds, ETF's, fixed-income funds, sector funds, international funds, money-market funds and balanced funds or have terms in their name not associated with active management or equity investment[7]. Specifically, we remove funds whose names contain strings, such as, "Index", "Idx", "Ix", "Indx", "Nasdaq", "Dow", "Mkt", "DJ", "S&P", "Barra", "100", "400", "500", "1000", "ETF",

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[1] Lo A. W., and MacKinlay A. C. 1990. Data-Snooping Biases in Tests of Financial Asset Pricing Models. *The Review of Financial Studies*, Vol. 3, No. 3, pp.431-467. (Publisher: Oxford University press for the Society for Financial Studies, Oxford, United Kingdom).

[2] Brock W., Lakonishok J., and LeBaron B. 1992.Simple technical trading rules and the stochastic properties of stock returns. *The Journal of Finance,* Vol.47, No. 5, 1731-1764. (Publisher: Wiley-Blackwell for the American Finance Association, Hoboken, New Jersey, United States).

[3] Lo A. W., and MacKinlay A. C. 1990. Data-Snooping Biases in Tests of Financial Asset Pricing Models. *The Review of Financial Studies*, Vol. 3, No. 3, p. 431 (431-467). (Publisher: Oxford University press for the Society for Financial Studies, Oxford, United Kingdom).

[4] "Data-snooping statistics" term was first used by Aldous (1989, p.252). Source: Aldous D. 1989. Probability approximations via the Poisson clumping heuristic. Springer-Verlag, New York. p.252 (269).

[5] White H. 2000. A reality check for data snooping. *Econometrica, Vol.* 68, No.5, pp.1097-1126. (Publisher: Wiley-Blackwell for the Econometric Society, Hoboken, New Jersey, United States).

[6] Romano P. J., and Wolf M. 2005. Stepwise multiple testing as formalized data snooping. *Econometrica,* Vol. 73, No. 4, pp.1237-1282. (Publisher: Wiley-Blackwell for the Econometric Society, Hoboken, New Jersey, United States).

[7] CRSP is missing information from 1998 through 2002 for most funds, so we check the information using the period from 1997 to determine the sample in 1999 through 2003.

"Exchange", "Balanced". Also we follow Jordan and Riley (2015) and exclude funds with the following strings in their names; "bond", "cash", "convertible", "cycle", "fixed", "government", "ishare", "lifestyle", "maturity", "money", "mortgage", "municipal", "powershare", "principal protection", "profund", "proshare", "rate", "real estate", "realty", "tax", "term", "treasury", "variable", "2005", "2010", "2015", "2020", "2025", "2030", "2035", "2040", "2045", "2050", "2055", "529". We select the funds based on the following Lipper codes EIEI, G, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, and SCVE.[12]

Next, we require that a fund have at least 80% of its assets invested in equity during the previous year[3]. The daily data file provides fund grouping variable (crsp_cl_grp), therefore we use this variable to combine multiple share classes of the same fund into a single fund. The assets of the combined fund are the sum of the assets held across all share classes. We weight fund returns by their assets held in each share class.

After the data treatment we are left with the sample that has 1843198 fund-day observations, contains 517 distinct funds that existed from January 2000 to December 2014.

Methodology

As we are investigating the performance of mutual funds, a robust methodology is needed to avoid misleading statistical inference due to data-snooping. To solve this problem we employ the "Reality Check" (RC) test introduced by White (2000) and its stepwise extension Step-RC test by Romano and Wolf (2005). The procedures allow us for intensive search for best performing mutual funds, while ensuring that the results are robust and do not result from mere luck. In this section, we briefly present all testing procedures.

We start by describing the RC test. Let $\varphi_k = \mathbb{E}(f_k), (k = 1, \dots, M)$, denote the performance measure of k-th model relative to the benchmark. f_k can be the mean return, Sharpe ratio or certainty equivalent return (CEQ) of the k-th mutual fund. The null hypothesis is that the best performing mutual fund does not have superior ability over the benchmark

$$H_0\colon \max_{k=1,\dots,M} \varphi_k \leq 0 \tag{1}$$

The rejection of the null hypothesis would imply existence of at least one fund that outperforms the benchmark. White (2000) bases a test of the null hypothesis on the maximum of the normalized sample average of $f_{k,t}$;

$$V_{RC} = \max_{k=1,\dots,M} \sqrt{n}\bar{f}_k, \tag{2}$$

where $\bar{f}_k = \frac{1}{n}\sum_{t=R}^{T} f_{k.t}$, $f_{k.t}$ is the t-th observation of f_k and n is the number of prediction periods indexed from R to T, such that $T = R + n - 1$. To compute the p-values of V_{RC} White (2000) suggests using stationary bootstrap technique introduced by Politis and Romano (1994)[4]. Let $f_k^*(b)$ be the b-th bootstrapped sample of f_k and $\bar{f}_k^*(b) = \frac{1}{n}\sum_{t=R}^{T} f_{k,t}^*(b)$ be its sample average. The empirical distribution of V_{RC}^* would be

$$V_{RC}^*(b) = \max_{k=1,..,M} \sqrt{n}\left(\bar{f}_k^*(b) - \bar{f}_k\right), \quad b = 1, \dots, B \tag{3}$$

Then the Reality check p-values are obtained by comparing V_{RC} with the quantile of the empirical distribution of V_{RC}^*

$$p_{RC} = \sum_{b=1}^{B} \frac{1_{\{V_{RC}^*(b) - V_{RC}\}}}{B}, \tag{4}$$

[1] Bradford D. J., and Riley B. T. 2015. Volatility and mutual fund manager skill. *Journal of Financial Economics,* Vol.118, No.2, pp.289–298. (Publisher: Elsevier, Amsterdam Netherlands).
[2] We repeat the screening procedure using CRSP (crsp_obj_cd), but the final sample of funds is unchanged.
[3] We use variable defined as "Per_com" in CRSP Survivorship- Bias- Free Mutual Fund Database.
[4] Politis D. N., and Romano P. J. 1994. The Stationary Bootstrap. *Journal of the American Statistical Association,* Vol.89, No. 428, pp.1303-1313. (Publisher: A Taylor & Francis for American Statistical Association, Milton Park, Abingdon, United Kingdom).

where $1_{\{\cdot\}}$ is indicator the function. The null hypothesis is rejected whenever the p-values are less than the specified significance level.

The test has a drawback that is the tests do not identify all models that reject the hypothesis. Rejecting the null hypothesis by the RC test only suggests that there exists at least one model that significantly surpasses the benchmark returns. Based on this drawback, Romano and Wolf (2005) construct stepwise RC test, which they call Step-RC test, that uses stepwise procedure to identify as many models with $\varphi_k > 0$ as possible. This test is practically more useful than the RC test, because investors are interested in as many outperforming funds as possible. The Step-RC test procedure consists of four steps;

1. Re-arrange $\bar{f_k}$ in descending order.
2. A top performance measure model would be rejected if $\sqrt{n}\bar{f_k}$ is greater than the bootstrapped critical value, where bootstrapping is computed as in the RC test using the complete sample. If no rejection of null hypothesis is detected the process stops; otherwise we move to the next step.
3. Next, remove $\bar{f_k}$ of the rejected models from the data and do the bootstrap procedure using the remaining data. In the new sample, a top model would be rejected if $\sqrt{n}\bar{f_k}$ is greater than the bootstrapped critical value from the sub-sample. If no rejection of null hypothesis is detected the process stops; otherwise we move to the next step.
4. Repeat the 3rd step until no more rejections are detected.

Performance Measures

In this paper we use three performance measures criteria to evaluate mutual fund performance: Mean return criterion, Sharpe ratio criterion and certainty equivalent (CEQ) return criterion. Specifically let $r_{k.t}$ denote fund k's excess net return in month t, $r_{j.t}$ be the benchmark j's excess return and r_t^f be the risk free rate. We first denote $r_{k,t}^e = r_{k,t} - r_t^f$ and $r_{j,t}^e = r_{j,t} - r_t^f$ as the excess return for each fund and each benchmark. Then, the mean return criterion used in our test is calculated as follows;

$$f_k^{(1)} = \frac{1}{n}\sum_{t=R}^{T}\left(r_{k,t}^e\right) - \frac{1}{n}\sum_{t=R}^{T}\left(r_{j,t}^e\right) \tag{2.1}$$

Second performance measure used in our analysis is Sharpe Ratio criterion.

$$f_k^{(2)} = \frac{\frac{1}{n}\sum_{t=R}^{T} r_{k,t}^e}{\hat{\sigma}_k} - \frac{\frac{1}{n}\sum_{t=R}^{T} r_{j,t}^e}{\hat{\sigma}_j}, \tag{2.2}$$

Where $\hat{\sigma}_k^2$ is the fund k's estimated standard deviation and $\hat{\sigma}_j^2$ is benchmark j's estimated standard deviation.

Next, we use certainty-equivalent (CEQ) returns as a performance measure. The certainty equivalent rate of return for a risky portfolio is the return such that the investor is indifferent between that portfolio and earning a certain return. We compute the CEQ return as follows;

$$r_k^{CEQ} = \frac{1}{n}\sum_{t=R}^{T} r_{k,t}^e - \frac{\gamma}{2}\hat{\sigma}_k^2 \tag{2.3}$$

r_k^{CEQ} depends on the characteristics of the portfolio and the investor's risk tolerance. In our analysis we set the risk aversion coefficient $\gamma = 1$. Then the certainty-equivalent (CEQ) performance measure would be difference between CEQ return of the fund k and the benchmark j:

$$f_k^{(3)} = r_k^{CEQ} - r_j^{CEQ} \tag{2.4}$$

Benchmarks

We start by providing an overall view of the performance of the mutual funds over the January 2000 to December 2014 period. We follow Wermers (2000) and compare the equal and value weighted daily returns of mutual funds to the daily returns on two market indices during the same period: S&P 500 index and the CRSP NYSE/AMEX/Nasdaq value weighted portfolio[1]. We also compare the performance of the mutual funds in the sample to one of the biggest index funds, Vanguard Index 500 fund. Wermers (2000) notices that it is often claimed by Vanguard 500 fund managers that the fund outperforms the average mutual fund due to the low costs and low trading activity of the fund and that the money managers who actively chase stocks do not have the ability to find stocks that outperform the market portfolio by enough to recover their expenses and trading costs. Therefore we find interesting to compare the mutual funds included in the sample to the biggest Index fund that closely tracks the market indices.

Table 1 shows that mutual funds included in our sample have higher daily returns and Sharpe ratios, however, they are more volatile having the highest standard deviation, the highest decline and highest incline during a day, which is not surprising as our sample includes growth oriented and aggressive funds. CRSP value weighted index has the highest level of returns among benchmarks, but has higher standard deviation. It is noteworthy that Vanguard 500 index fund closely tracks the S&P500 index having slightly higher returns on daily basis. Overall three benchmarks have similar skewness and kurtosis.

Table 1

Summary Statistics of Mutual Fund and Benchmark Portfolios

	EW Fund Portfolio	VW Fund Portfolio	S&P500	CRSP VW Portfolio	VAN500
Mean (bps)	2.1	3.8	0.21	1.3	0.86
Std Dev (bps)	135	932	127	128	127
Sharpe Ratio	0.0154	0.0041	0.0017	0.0103	0.0068
Max (bps)	2440	2435	1156	1151	1158
Min (bps)	-1480	-1477	-903.9	-899.9	-902.9
Skewness	-0.011	-0.012	0.131	0.040	0.131
Kurtosis	6.547	6.552	8.250	7.395	8.239

Note: This table presents the mean (bps), standard deviation (bps), Sharpe Ratio, Maximum, Minimum values and Skewness and Kurtosis for benchmark returns; S&P500, CRSP VW Portfolio, Vanguard 500 Index Fund and for the equally weighted (EW) and value weighted (VW) mutual fund portfolio. The sample period is from January 2000 to December 2014.

Empirical Results

In this section we identify the best-performing mutual funds using three performance measures against three benchmarks. We start by showing the results that do not account for data snooping. Table 2 presents the number and the percentage of the funds in the sample that outperform S&P 500 , CRSP VW Portfolio and Vanguard 500 Index fund benchmarks under mean return, Sharpe ratio and certainty-equivalent return (CEQ) criteria without considering the data-snooping bias. The sample of mutual funds includes 517 distinct funds spanning the period from January 2000 to December 2014. From the table it is obvious that most of the funds outperform the given benchmarks, except when the performance measure is CEQ. For example, out of 513 funds 499 funds outperform S&P500 index under mean return criterion, which accounts for 96% of the funds included in our sample. Also, 72% and 86% of the funds included in the sample outperform CRSP NYSE/AMEX/Nasdaq index and Vangurad 500 index respectively. When we use Sharpe ratio as a criterion there are 497 funds that outperform S&P 500 index, 365 funds have superior Sharpe Ratio over the one of NYSE/AMEX/Nasdaq portfolio and 444 funds that outperform the Vanguard 500 index fund. In the end, when the Certainty-Equivalent Return criterion is used the number of the funds that outperform the benchmarks almost halves. Now only 43%, 37% and 39% of funds included in the sample outperform S&P500, CRSP VW portfolio and Vanguard500 index fund respectively. Now only 43%, 37% and 39% of funds included in the sample outperform S&P 500, CRSP VW portfolio and Vanguard 500 index fund respectively. Overall, results show that most of the funds are able to outperform given benchmarks, when the data-snooping is not controlled. Therefore the inference made from these results might be misleading.

[1] Wermers R. 2000. Mutual fund performance: An empirical decomposition into stock picking talent, style, transaction costs, and expenses. *The Journal of Finance,* Vol. 55, No 4, pp.1655-1695. (Publisher: Wiley-Blackwell for the American Finance Association, Hoboken, New Jersey, United States).

Table 2

Mutual fund performance without controlling for data-snooping

	S&P 500		CRSP VW		VAN 500	
	Number	Percentage (%)	Number	Percentage (%)	Number	Percentage (%)
Mean	499	96%	375	72%	448	86%
Sharpe Ratio	497	96%	365	70%	444	85%
CEQ	224	43%	192	37%	206	39%

Note: This table presents the number and the percentage of the funds in the sample that outperform S&P500 , CRSP VW Portfolio and Vanguard500 Index benchmarks under Mean Return, Sharpe Ratio and Certainty-Equivalent Return (CEQ) criteria without considering the data snooping bias. The sample of mutual funds includes 517 distinct funds spanning the period from January 2000 to December 2014.

Next, we show the results of empirical analysis which accounts for the data-snooping. Table 3 reports the results for the performance of the best performing mutual fund under the mean return criterion (Panel A), Sharpe ratio criterion (Panel B) and certainty-equivalent return criterion (Panel C). For each benchmark, the RC p-values and the corresponding nominal *p*-values are reported.

Table 3

Mutual Fund Performance After Controlling for Data Snooping

	Panel A : Mean Return Criterion		
	Reality Check		
Benchmark	Nominal	RC	Step-RC
S&P500	0.014	0.099	-
VAN500	0.041	0.184	-
NYSE/AMEX/Nasdaq	0.049	0.213	-

	Panel B : Sharpe Ratio Criterion		
	Reality Check		
Benchmark	Nominal	RC	Step-RC
S&P500	0	0.01	10
VAN500	0.003	0.02	3
NYSE/AMEX/Nasdaq	0.001	0.028	1

	Panel C : Certainty-Equivalent Return (CEQ) Criterion		
	Reality Check		
Benchmark	Nominal	RC	Step-RC
S&P500	0	0.16	-
VAN500	0.001	0.271	-
NYSE/AMEX/Nasdaq	0	0.033	-

Note: This table presents the performance of the best mutual fund under the Mean Return criterion (Panel A), the Sharpe ratio criterion (Panel B) and Certainty-Equivalent Return criterion (Panel C) using a daily return from January 2000 to December 2014. For each benchmark the table shows the "Reality Check" (RC) *p*-values along with the corresponding nominal p-values. The nominal p-values are obtained by applying the RC to the best mutual fund only, without correcting for data-snooping biases. In addition, (whenever the RC *p*-values are significant), the numbers of outperforming rules identified by the stepwise procedure are listed in the column Step-RC.

The nominal *p*-values are obtained by applying the RC testing procedure to the best mutual fund only, without correcting for data-snooping biases. Also, when the RC *p*-values are significant at 5% significance level we report the number of these significant mutual funds obtained from stepwise RC. The *p*-values are calculated using stationary bootstrap procedure of Politis and Romano (1994), where the number of bootstraps is set to 1000 ($B = 1000$) and the smoothing parameter q is equal to 1.

Under the mean return criterion, the nominal *p*-values for all three benchmarks are below 5% significance level; hence we can reject the null hypothesis of no outperformance by the best mutual funds relative to the benchmarks. This result might not be entirely unexpected, as we saw previously that there is large number of funds that outperform benchmark returns without controlling for the data snooping bias. In sharp contrast, the data-snooping corrected RC *p*-values are very high for all three benchmarks, which means that there is no single fund performance that can reject the null hypothesis.

The results for the best performing mutual fund under Sharpe Ratio are depicted in Panel B. Again the nominal *p*-values are well below 0.05 level. The RC test also shows significant *p*-values, so we reject the null hypothesis. The stepwise counterpart of the RC test detect 10 funds outperforming S&P 500 index, 3 funds that outperform Vanguard 500 index fund and only 1 fund that was able outperform CRSP VW portfolio.

In the end we show the results for the best performing mutual fund under the certainty-equivalent return (CEQ) performance measure. As in the previous cases nominal p-values are close to zero. Reality Check test fails to reject the hypothesis that there exists at least one fund that can outperform any chosen benchmark. Therefore the Step-RC detects no outperforming funds.

These results are strikingly different relative to the results without controlling for the data snooping. In summary, we find that most mutual funds, when considered in isolation, produce superior performance relative to the benchmarks. This finding is consistent with the hypothesis that the mutual funds possess superior skills. However, once we control for effects of data snooping, we no longer observe superiority. These findings illustrate the effect of data-snooping on statistical inference and underline the importance of correcting for data-snooping biases.

Conclusion

This article examines the performance of the mutual funds while controlling for potential effects of the data snooping. We examine a sample of U.S. actively managed equity mutual funds by applying White's (2002) "Reality Check" (RC) test. We extend the analysis to detect the all outperforming mutual funds using the stepwise extensions of RC test developed by Romano and Wolf (2008).

We find that when the data snooping is not controlled, most of the actively managed mutual funds outperform their counterpart benchmarks, hence supporting the existence of managerial skill. After applying the RC test to adjust for the effects of data snooping, the number of outperforming mutual funds decreases dramatically. This means that the superior performance of many mutual funds relative to the benchmarks is simply an outcome of luck and not the real managerial skill. However, tests detect few mutual funds that have superior ability to constantly beat the markets. The results are robust relative to all included benchmarks. These findings illustrate the effect of data snooping on statistical inference and underline the importance of correcting for data snooping biases.

ՏՎՅԱԼՆԵՐԻ ՈՒՍՈՒՄՆԱՍԻՐՈՒԹՅԱՆ ԸՆԹԱՑՔՈՒՄ ԿՈՂՄՆԱԿԱԼՈՒԹՅԱՆ ԴՐՍԵՎՈՐՄԱՆ ԱԶԴԵՑՈՒԹՅՈՒՆԸ ՓՈԽԱԴԱՐՁ ՖՈՆԴԵՐԻ ԳՈՐԾՈՒՆԵՈՒԹՅԱՆ ՎՐԱ

ԳԵՎՈՐԳ ՀԱՅԿԻ ԳՐԻԳՈՐՅԱՆ
Շանհայի ֆինանսների և տնտեսագիտության համալսարանի ասպիրանտ

Համառոտագիր

Այս հոդվածում փորձ է արվում քանակական արտահայտությամբ ներկայացնել տվյալների մշակման (Data Mining) հնարավոր կողմնակալության ազդեցությունն ԱՄՆ-ի ակտիվ կառավարվող փոխադարձ ֆոնդերի կատարողականի վրա: Այս նպատակով հոդվածում օգտագործվում են փորձարկման մեթոդներ, մասնավորապես՝ Ուայթի (2000) «Իրականության ստուգում» և Ռոմանո և Վոլֆի (2005) «Իրականության ստուգում» թեստի փուլային ընդլայնման մեթոդը: Թեստերի արդյունքները վկայում են, որ, երբ տվյալների ուսումնասիրության հնարավոր կողմնակալությունը հաշվի չի առնվում, փոխադարձ ֆոնդերի գործունեությունը կարող է վիճակագրորեն նշանակալի լինել համապատասխան ուղենիշների նկատմամբ: Սակայն, երբ մենք ձերբազատվում ենք տվյալների ուսումնասիրության հնարավոր կողմնակալության ազդեցությունից, գերազանց կատարողականով աշխատող փոխադարձ ֆոնդերի թվաքանակը կտրուկ նվազում է արձանագրում, իսկ սա մատնանշում է, որ փոխադարձ ֆոնդերի մեծ մասի բարձր արդյունավետությունը լոկ պատահականության արդյունք է, և միայն փոքր թվով ֆոնդեր են տիրապետում իրական հմտության՝ շուկայում առաջատար դիրքեր գրավելու տեսանկյունից: Արդյունքները փաստում են կողմնակալության ճշգրտման կարևորության մասին:

Բանալի բառեր. *փոխադարձ հիմնադրամներ, կատարողական, տվյալների ուսումնասիրության կողմնակալություն, արդյունավետության ցուցանիշներ, ուղենշային ցուցիչներ, «իրականության ստուգում» թեստ, «փուլային իրականության ստուգում» թեստ:*

ВОЗДЕЙСТВИЕ ПРОЯВЛЕНИЯ СУБЪЕКТИВИЗМА В ПРОЦЕССЕ ДАТАМАЙНИНГА НА ДЕЯТЕЛЬНОСТЬ ПАЕВЫХ ИНВЕСТИЦИОННЫХ ФОНДОВ

ГЕВОРГ АЙКОВИЧ ГРИГОРЯН
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Аннотация

В статье автор попытался представить в количественном выражении воздействие возможного субъективизма на производительность активно управляемых паевых инвестиционных фондов США в процессе датамайнинга. С этой целью в статье использованы тесты Уайта «Проверка реальности («Reality Check» (RC) 2000), а также его ступенчатая модификация - тест Романа и Вульфа (2005). Результаты тестов свидетельствуют о том, что без коррекции датамайнинга большое количество фондов способно превзойти эталонные показатели. Однако, после коррекции датамайнинга количество фондов, превосходящих эталонные показатели, резко уменьшается.Это указывает на то, что производительность большинства паевых фондов - результат чистой случайности, и лишь небольшое количество фондов обладает достаточным опытом для занятия лидирующих позиций на рынке. Результаты свидетельствуют о важности корректировки субъективизма.

Ключевые слова: *паевые фонды, производительность, субъективизм при исследовании данных, показатели эффективности, эталонные индикаторы, тест «проверка реальности», тест « поэтапная проверка реальности».*

THE EFFECTS OF DATA-SNOOPING BIAS ON MUTUAL FUND PERFORMANCE

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Abstract

In this article we examine the performance of mutual funds while controlling for the data snooping bias. We use White's (2000) "Reality Check" (RC) and its stepwise extension Romano and Wolf's (2008) Step-RC tests. We find that without controlling for data snooping bias large number of actively managed equity funds are able to outperform benchmark indices. After controlling for data snooping bias the number of outperforming mutual funds dramatically decreases, indicating that only few mutual funds have superior ability to beat the markets. The results underline the importance of correcting for the data-snooping biases.

Keywords: *Mutual funds, performance, data snooping, performance measures, benchmark indices, "Reality Check" test, "Step-RC" test.*