

Working Paper No. 19-07

Economics and Finance Working Paper Series

Adiya Bayarmaa, and Guglielmo Maria Caporale

Style Consistency and Mutual Fund Returns: The
Case of Russia

March 2019

<http://www.brunel.ac.uk/economics>

STYLE CONSISTENCY AND MUTUAL FUND RETURNS: THE CASE OF RUSSIA

Adiya Bayarmaa
International College of Economics and Finance (ICEF)
Higher School of Economics (HSE), Moscow

Guglielmo Maria Caporale
Department of Economics and Finance
Brunel University London

March 2019

Abstract

This paper carries out style analysis for Russian mutual funds using monthly data from the National Managers' Association over the period January 2008-December 2017; specifically, it applies the RSBA method developed by Sharpe (1992) for evaluating the impact of style on returns, and uses the Style Drift Score (SDS) introduced by Idzorek (2004) as a measure of a fund's style drifting activity. The main findings can be summarised as follows. In the Russian case there is a significant positive relationship between style consistency and profitability of funds. Further, Russian funds are characterised by a high level of style drift, namely deviations from the investment strategy declared at the time of registration as required by Russian law.

JEL classification: C23, G14, G19

Keywords: mutual funds, style consistency, performance, Russia

Corresponding author: Professor Guglielmo Maria Caporale, Department of Economics and Finance, Brunel University London, Uxbridge UB8 3PH, UK.
Email: Guglielmo-Maria.Caporale@brunel.ac.uk

1. Introduction

Institutional investors (mutual funds) are key players in financial markets: they collect cash from small individual investors and then invest large sums of money in financial assets on behalf of their shareholders. From the perspective of an individual investor, investing in mutual funds can be beneficial in several ways. First, mutual funds can be more cost effective in terms of time and effort spent on analysing financial assets and constructing portfolios: fund managers, because of their greater market knowledge and experience, have advantages in stock-picking and asset allocation activities that can generate higher returns and reduce risk. Second, individual investors can benefit from scale effects: by investing in mutual funds, they can own a diversified portfolio of assets at a fraction of the cost they would incur if they constructed it themselves; in other words, mutual funds eliminate the resource constraint faced by individual investors for portfolio diversification.

Considering these benefits, it may seem natural that individual investors should invest in mutual funds, choosing a specific fund on the basis of the skills of their managers and the additional costs of investing in that fund relative to the returns it generates for the investor. There exists a large literature analysing the determinants of the performance of mutual funds, including management skills. In particular, style analysis investigates how a fund's investing style or set of investment strategies (and any deviations from its style over a continuous time period) affects its long-term returns. It is normally thought that funds that stick to their initial strategy and have a more consistent style will perform better in the long run compared to those that constantly shift between different styles (which is commonly known as style-drifting) or do not even follow a particular style, and, instead, concentrate on momentum investing. There are various possible reasons for this expectation. One of them is the fact that style-drifting funds may incur higher transaction costs owing to higher asset turnover, because in trying to outperform the market they engage in active portfolio management. On the contrary, style-consistent funds are less concerned about stock-picking and generally tend to replicate their own type of portfolio and engage in passive portfolio management. Also, according to Barberis and Shleifer (2003) and Huang et al.

(2008), they are less prone to asset selection errors and altering the degree of risk of their portfolio, which results in higher returns. On the whole, the empirical evidence of the effects of style consistency on the performance of mutual funds is mixed.

This paper focuses on Russian mutual funds with the aim of establishing whether or not style consistency generates higher returns in this particular case. Its findings will shed further light on this issue, and will also be directly relevant to financial regulators, providing useful information to the Bank of Russia on whether or not it should impose restrictions on the operation of mutual funds depending on their style consistency. The rest of the paper is structured as follows: Section 2 briefly reviews the relevant literature; Section 3 describes the data and the methodology; Section 4 presents the empirical results; Section 5 offers some concluding remarks.

2. Literature Review

The seminal contributions are due to Sharpe (1992), Idzorek (2004) and Brown and Harlow (2009). The first paper introduced return-based style analysis (RBSA) as a feasible and effective way of evaluating fund portfolio styles which is based on regressing portfolio returns on several style indices using GLS with appropriate restrictions. Specifically, Sharpe (1992) considered three different RBSA models, namely “quadratic programming”, “constrained regression” and “unconstrained regression” respectively, where the first one requires the regression coefficients to lie between 0 and 1 and sum up to one, the second one only that they sum up to one, and the third one is a simple OLS regression without any restrictions. Idzorek (2004) put forward the Style Drift Score (SDS) as a measure of a fund’s style drifting activity, which is calculated as the square root of the variance of the fund’s style index beta coefficients. Brown and Harlow (2009) analysed US equity mutual funds between January 1980 and December 2006, measured style consistency using both RBSA and holdings-based style analysis methods (the latter being based on a fund’s portfolio structure rather than its past returns), and assessed its impact on a fund’s future performance. They concluded that style consistency, measured with either method, is a good predictor of a mutual fund’s future performance.

Various other papers on this topic have been published in recent years. Cao (2017) investigated style drift in US small cap funds and found that this increased between 2003 and 2010, when there was a highly significant 3% alpha. Cumming (2009) studied style drift in private equity and reported that a fund's tendency to style drift is positively correlated with the fund manager's age and market conditions. Galloppo (2017) showed that company fundamentals do not have significant effects on style drift in US equity funds. Herrmann (2016), using monthly returns data on 2631 US equity funds between October 1998 and December 2009, found that a fund's style shifting activity, measured as the difference between multi-factor regression betas from two consecutive quarters, is a useful measure of a fund's performance. Kurniawan (2016) investigated the relationship between fund governance and style drift in US mutual funds and reported that the effectiveness of fund governance is negatively related to a fund's style drift; further, funds whose managers have more decision-making power are more likely to exhibit style drift than those whose owners are independent from the managers. Moneta (2015) studied 969 US bond market funds during the period from 1997 to 2006 and concluded that actively managed funds outperformed passive funds by 1% each year. Papadamou (2017) examined the 8 largest Japanese equity funds during the period 2015-2016 and found that only 2 of these actively managed funds outperformed the market.

3. Data and Methodology

Our data source is the Russian mutual fund database of the National Managers' Association, a subdivision of NAUFOR, Russia's non-governmental organisation that represents the interests of Russia's financial market participants at home and internationally. This database includes monthly net assets and share prices for a total of 1658 funds between January 2008 and December 2017. During this period, Russian funds were required by law to register declaring to which of the following categories they belonged:

- Stock – primarily investing in stocks of public companies listed on the Moscow Stock Exchange;

- Venture capital – primarily investing in shares of private companies;
- Money Market – primarily investing in short-term bonds or bank deposits;
- Stock index – their portfolio aims to replicate the structure of a given stock index;
- Bond index – their portfolio aims to replicate the structure of a given bond index;
- Mortgage – primarily investing in mortgages;
- Mixed investment – investing both in stocks of public and private companies and bonds;
- Direct investment – funds that can invest both in private and public companies but predominantly invest in public companies listed on stock exchanges;
- Credit – engaging in direct lending to individuals and to companies;
- Real estate – primarily investing in commercial buildings and private housing;
- Bond market – primarily investing in bonds with longer maturities;
- Commodity – primarily investing in gold, silver, and other precious metals;
- Art – primarily investing in art objects.

According to Russian law, funds are allowed to invest up to 50% of their resources into assets other than the category under which they have registered. For example, a fund registered as a commodity fund is obliged to invest at least 50% of its financial resources in commodities, but can freely allocate the remaining 50% to other assets such as stocks, bonds etc.; this makes it possible to engage in style drifting without breaking the law.

We use the categories above as a proxy for investment style and carry out style analysis only for funds for which share prices are available for at least 13 consecutive months. We also drop funds registered under real estate, venture capital, art, mortgage and credit because there are no appropriate style indices in such cases. In this way, the

sample is reduced from 1658 to 924 funds. Further, we combine similar categories as follows: stock, stock index, direct and mixed investment categories into a single “stock” category; bond market and bond index into a single “bond” category; this yields 4 categories to consider: stock, bond, money, commodity. We also decided to add an additional “international” category that includes stock funds investing in the international rather than the domestic markets and therefore incurring an additional exchange rate risk. The number of funds in each category by year is reported in Table 1, their distribution into categories is shown in Figure 1, and their returns with some descriptive statistics are displayed in Table 2.

[INSERT TABLE 1]

[INSERT FIGURE 1]

[INSERT TABLE 2]

We choose the “constrained regression” version of the RBSA model and estimate rolling-window regressions over 12 months. Because this specification only requires that all coefficients add up to one, each beta coefficient individually can take both positive and negative values. Thus, this model specification allows funds to short the market indices. The regression is the following:

$$Return_{it} = \alpha_{it} + \beta_{1t}MICEX_t + \beta_{2t}RCB5Y_t + \beta_{3t}RGB5Y_t + \beta_{4t}Gold_t + \beta_{5t}USD_t + \epsilon_{it}$$

(1)

where:

- $Return_{it}$ – monthly returns of fund i during the 12-month period ending at t ;
- $MICEX_t$ – monthly returns of the Moscow Stock Exchange Full Return Index during the 12-month period ending at t ;
- $RCB5Y_t$ – monthly returns of the Moscow Stock Exchange Corporate 5-Year Bond Index during the 12-month period ending at t ;
- $RGB5Y_t$ – monthly returns of the Moscow Stock Exchange Government 5-Year Bond Index during the 12-month period ending at t ;
- $Gold_t$ – monthly percentage changes of the Bank of Russia’s gold buy/sell quotes;
- USD_t – monthly percentage changes of the Bank of Russia’s USD buy/sell quotes.

The model coefficients measure the effect of each style index on the fund's returns. The indices for each category were chosen as follows: MICEX - stock funds; RCB5Y - bond funds; RGB5Y - money market; Gold - commodity; USD - "international". Table 3 reports summary statistics for the style indices, Figure 2 displays the series, and Figure 3 their correlations; although they appear to be highly correlated, according to Sharpe (1992) they can still be used for the analysis as long as they have different standard deviations.

[INSERT FIGURE 2]

[INSERT FIGURE 3]

[INSERT TABLE 3]

Next, we define style consistency in terms of a fund's maximum beta coefficient – betamax:

betamax =

$$\left. \begin{array}{l} IFmax_i \left(E(\beta_{1t}), \dots, E(\beta_{jt}) \right) \neq Styleindex_i, fundiisstyleinconsistent, j = 1,2,3,4,5 \\ IFmax_i \left(E(\beta_{1t}), \dots, E(\beta_{jt}) \right) = Styleindex_i, fundiisstyleconsistent, j = 1,2,3,4,5 \end{array} \right\} \quad (2)$$

We first identify the beta with the highest average value over the sample period considered for each fund. Then we compare it to the category style index and define a fund as style consistent if its beta is the same as the fund's category index, or style drifting otherwise. Following Idzorek (2004), style drift is measured using the SDS statistic, which is the square root of the sum of the variance of the beta coefficients:

$$SDS = \sqrt{VAR(\beta_{1t}) + VAR(\beta_{2t}) + VAR(\beta_{3t}) + VAR(\beta_{4t}) + VAR(\beta_{5t})} \quad (3)$$

where $VAR(\beta_{jt})$ represents the variance of each estimated coefficient from the rolling regression. The higher the SDS, the higher is the style drift of a fund.

We then divide funds into four different groups on the basis of style consistency and style drift and compare their mean returns. The median SDS was chosen as a threshold value for style drift, and style consistency is measured as in (2). The four groups are the following:

1. Style-consistent, low style-drifting funds – these funds strictly follow their style and almost never deviate from it;

2. Style-consistent, high style-drifting funds – these funds generally follow their style, but at times deviate from it;
3. Style-inconsistent, low style-drifting funds – these funds generally do not follow their style, but are consistent according to some “unknown” style (as, for instance, in the case of a fund initially classified as a corporate bond market fund, but consistently showing returns comparable to stock market index funds);
4. Style-inconsistent, high style-drifting funds – these funds do not follow their style and exhibit inconsistent behavior resulting from active portfolio management.

4. Empirical Results

Table 4 presents summary statistics for the style index beta coefficients. They indicate the presence of shorting, since there are negative betas for each style index. Values of beta greater than one correspond to cases when funds, instead of short selling, engage in marginal trading, i.e. use external credit to finance purchases of financial assets. Since each of the beta coefficients represents a share of the volatility of a particular style index, the summary statistics of Table 4 also suggest that, in general, Russian funds trade more actively in the corporate bond market than in the stock market.

[INSERT TABLE 4]

Figure 4 shows the distribution of the maximum betas for different types of funds. It is interesting to note that 608 out of 924 funds in Russia appear to be style inconsistent (see Figure 5). By comparing Figure 1 and Figure 4 it becomes apparent that most of the funds that were initially categorised as stock funds actually exhibit returns patterns more similar to those for the bond index ones.

[INSERT FIGURE 4]

[INSERT FIGURE 5]

Table 5 reports the mean and standard deviation of returns, again for the four different categories, and Table 6 the p-value of t-tests for differences in the mean return between categories. It can be seen from Table 5 that style inconsistent funds with a high

style drift (IHS) exhibit the highest volatility, but only have the second highest portfolio returns, while style consistent funds with a low style drift (CLS) performed, on average, 17% better than other funds, a result which is statistically significant at the 1% level and is consistent with the findings of Brown and Harlow (2009) and other researchers.

[INSERT TABLE 5]

[INSERT TABLE 6]

One of the possible explanations for the better performance of the CLS group of funds might be their distribution in terms of SDS. Figure 6 plots each fund's cumulative return against its SDS score. It can be seen that style-consistent funds (blue dots) are generally clustered in the southeast area of the graph, while style-inconsistent funds (red dots) are concentrated in the northwest area.

[INSERT FIGURE 6]

5. Conclusions

Investment funds play an important role in financial markets and for the economy as a whole by collecting resources from individual investors and reinvesting them more efficiently, minimising risk and building portfolios at a lower cost. One of the determinants of their performance is thought to be their investment style. This paper carries out style analysis for Russian mutual funds, for which no previous evidence was available, using monthly data from the National Managers' Association over the period January 2008-December 2017; specifically, it applies the RSBA method developed by Sharpe (1992) for evaluating the impact of style on returns, and uses the Style Drift Score (SDS) introduced by Idzorek (2004) as a measure of a fund's style drifting activity.

The main findings can be summarised as follows. In the Russian case there exists a significant positive relationship between style consistency and profitability of funds. Further, Russian funds appear to be characterised by a high level of style drift and inconsistency, i.e. deviations of their investment strategies from those declared at the time of registration as required by Russian law. These results are similar to those reported by Brown and Harlow (2009) and other reserchers that also find a statistically significant and positive relationship between style consistency and fund performance.

They have some important policy implications for the Bank of Russia as a financial overseer and regulator, specifically they suggest that it should impose restrictions on the style-drifting behaviour of funds and provide incentives for them to become more style-consistent.

References

- Barberis, N. and Shleifer, A. (2003), Style investing, *Journal of Financial Economics*, **68**, issue 2, p. 161-199.
- Brown K., Harlow W., Zhang H (2009), Staying the Course: The Role of Investment Style Consistency in the Performance of Mutual Funds. Working paper. University of Texas, Austin.
- Cao, C., Iliev, P. and Velthuis, R. (2017), Style drift: Evidence from small-cap mutual funds, *Journal of Banking & Finance*, **78**, issue C, p. 42-57.
- Cumming, D., Fleming, G. and Schwienbacher, A. (2009), Style Drift in Private Equity, *Journal of Business Finance & Accounting*, **36**, issue 5-6, p. 645-678.
- Galloppo, G. and Trovato, G. (2017), Fundamental driver of fund style drift, *Journal of Asset Management*, **18**, issue 2, p. 99-123.
- Herrmann, U., Rohleder, M. and Scholz, H. (2016), Does style-shifting activity predict performance? Evidence from equity mutual funds, *The Quarterly Review of Economics and Finance*, **59**, issue C, p. 112-130.
- Huang, J., C. Sialm, and H. Zhang (2008), Risk shifting and mutual fund performance, Working Paper, University of Texas.
- Idzorek, and Bertsch, F. (2004), The Style Drift Score. *Journal of Portfolio Management*, **31**, p. 76-83.
- Kurniawan, M., How, J. and Verhoeven, P. (2016), Fund governance and style drift, *Pacific-Basin Finance Journal*, **40**, issue PA, p. 59-72.
- Moneta, F. (2015), Measuring bond mutual fund performance with portfolio characteristics, *Journal of Empirical Finance*, **33**, issue C, p. 223-242.
- Sharpe, W.F. (1992), Asset allocation: Management style and performance measurement. *The Journal of Portfolio Management*, **18**, p. 7-19.

Table 1. Number of funds at the end of each year

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Stock	518	492	482	513	492	471	418	369	338	293
Bond	95	82	79	88	93	104	98	92	85	79
Money market	11	11	12	13	12	13	14	14	12	8
International	2	2	2	4	5	5	5	5	5	5
Commodity	1	4	2	5	8	8	8	7	8	7
Total	627	591	577	623	610	601	543	487	448	392

Figure 1. Distribution of funds into categories

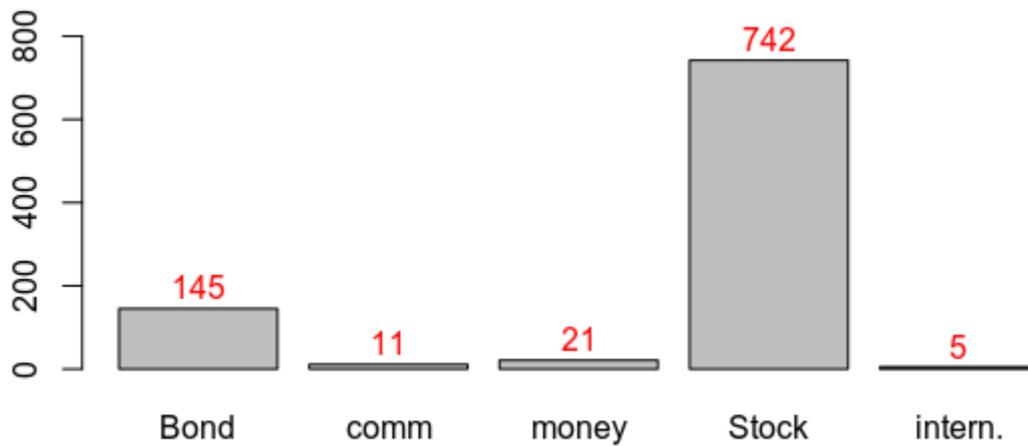


Table 2. Fund returns and descriptive statistics

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Mean	-0.0626	0.0568	0.0192	-0.0124	0.0039	0.0016	0.0028	0.0176	0.0123	0.0024
St.dev	0.0944	0.0540	0.0382	0.0412	0.0369	0.0249	0.0247	0.0359	0.0148	0.0182
Skewness	-1.1556	0.3039	-0.6106	-0.1216	-0.7085	0.1214	0.1681	1.6188	1.3880	-1.2090
Kurtosis	5.2336	3.4552	4.6508	3.6021	5.3603	2.7380	4.7235	7.9066	5.4185	5.2872

Table 3. Style indices summary statistics

	RCB5Y	RGB5Y	MICEX	Gold	USD
Mean	0.007	0.004	0.004	0.013	0.008
StdDev	0.013	0.012	0.074	0.070	0.052
Skewness	-2.387	-1.512	-0.600	1.115	1.271
Kurtosis	17.995	11.832	5.840	6.187	6.928

Figure 2. Style index series

Jan 2008 / Dec 2017

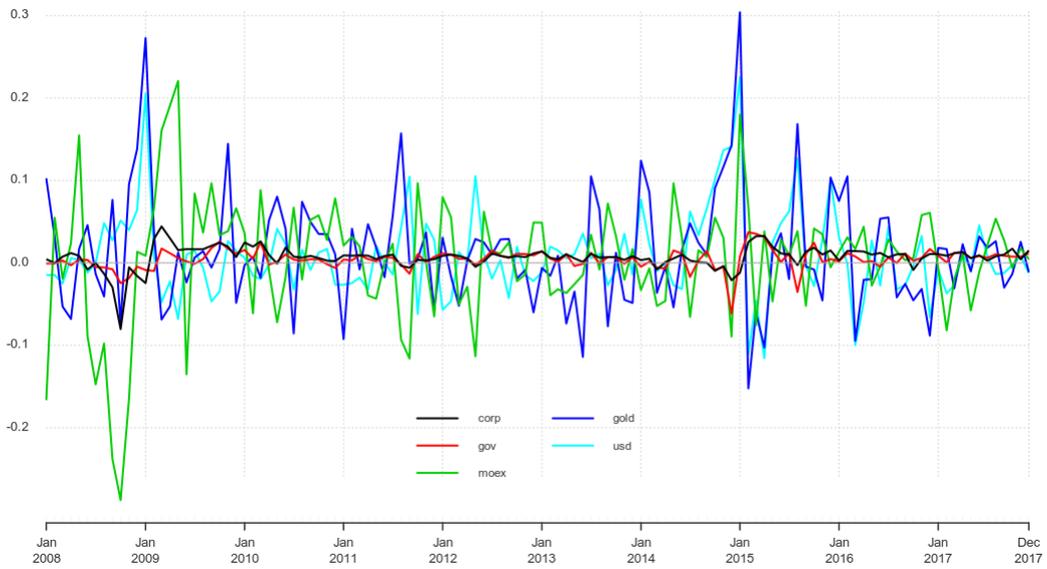


Figure 3. Style index correlations

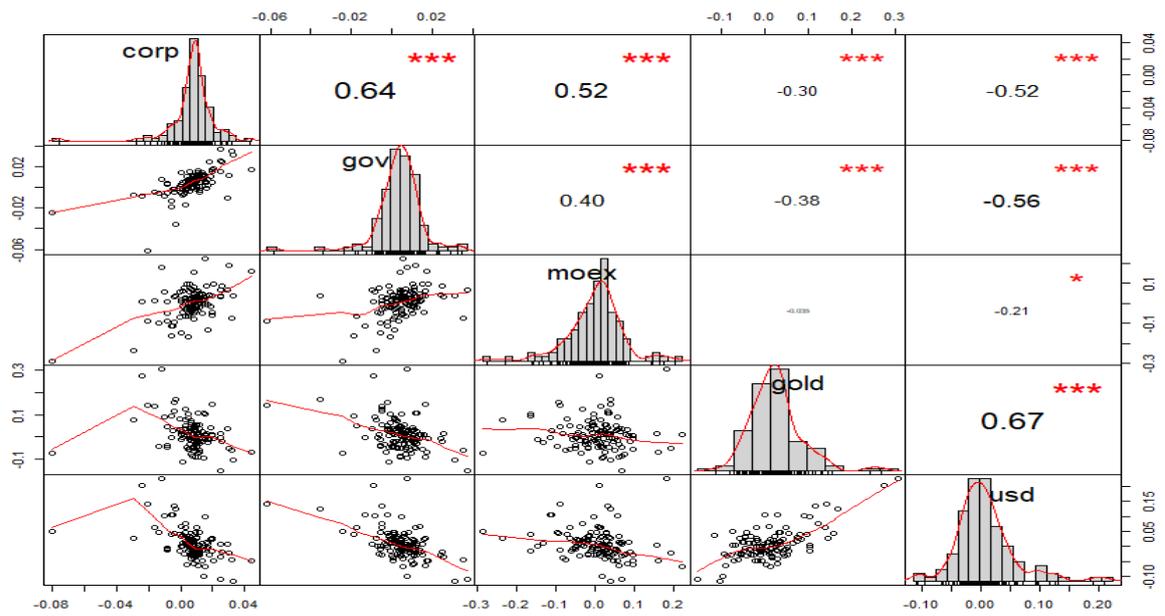


Table 4. Beta summary statistics

	RCB5Y	RGB5Y	MICEX	Gold	USD
Min.	-48.168	-26.114	-3.569	-4.987	-11.179
1st Qu.	0.299	-0.889	0.130	-0.037	-0.103
Median	0.776	-0.189	0.540	0.007	0.011
Mean	0.817	-0.314	0.483	0.029	-0.013
3rd Qu.	1.239	0.159	0.797	0.065	0.107
Max.	28.710	52.522	2.960	4.856	3.174
StDev	2.377	2.527	0.438	0.359	0.591
Skewness	-7.098	8.459	-1.770	1.175	-7.891
Kurtosis	223.862	225.696	21.050	94.767	148.463

Figure 4. Distribution of maximum betas for each type of fund

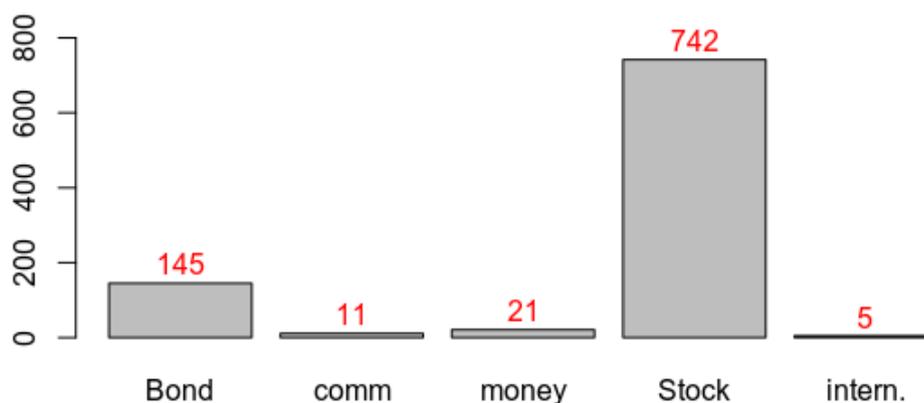


Figure 5. Style consistent/inconsistent funds

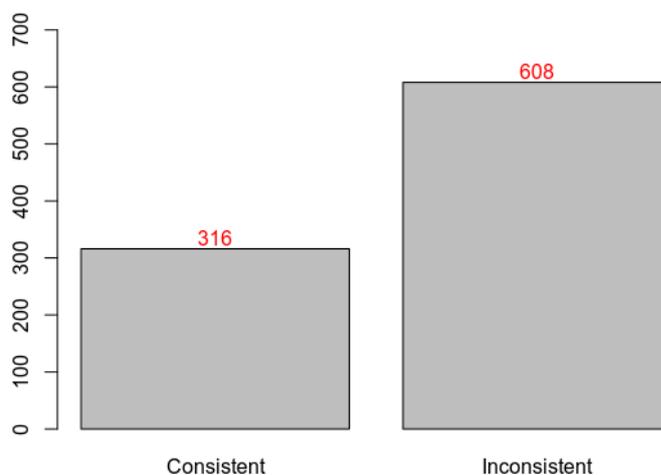


Table 5. Funds distribution, means and standard deviations of returns for the 4 groups of funds

	SD	MEAN	N
IHS	38.07%	21.11%	372
ILS	6.05%	10.23%	236
CHS	7.00%	19.31%	90
CLS	4.93%	37.92%	226

IHS – style-inconsistent funds with high SDS score

ILS – style-inconsistent funds with high SDS score

CHS – style-consistent funds with low SDS score

CLS – style-consistent funds with low SDS score

Table 6. P-value matrix of the t-test for the difference between group mean returns

	CLS	CHS	ILS	IHS
CLS	100.0%	0%	0%	0%
CHS	4.0007%*	100%	0%	0%
ILS	0.0002%**	30.8444%	100%	0%
IHS	2.6872%*	85.9167%	14.5328%	100%

* - significant at 5% level

** - significant at 1% level

Figure 6. Scatter-plot of funds' distribution in terms of SDS, Cumulative Returns and betamax

