NATIONAL RESEARCH UNIVERSITY
HIGHER SCHOOL OF ECONOMICS

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RUSSIAN MUTUAL FUNDS: SKILL VS. LUCK

BASIC RESEARCH PROGRAM

WORKING PAPERS

SERIES: FINANCIAL ECONOMICS
WP BRP 40/FE/2014

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Russian Mutual Funds: Skill vs. Luck [2]

Abstract

Our work is focused on Russian mutual funds managers' skills versus luck testing. Using the bootstrap procedure of Kosowski et al. (2007) we test Jensen's alpha significance for each fund. We found that only 5% of equity mutual funds do have skills. These results for the emerging Russian market are similar to previous studies of developed markets. Interestingly, skilled funds are not characterized with the extremely high alpha. This leads to an unexpected conclusion: an investor should avoid funds with a very high alpha.

Keywords: asset management, Russian stock market, skill, mutual fund

JEL: G230, C120

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[2]Thanks to Igor Zakharov, Anton Semushin, Marina Oskolkova, Iuliia Naidenova, Elena Shakina, Maria Molodchik, Sergei Kurochkin, Sergei Ivliev, participants of NRU HSE – Perm scientific seminar and participants NRU HSE April conference for valuable comments. This study (research grant No 14-01-0071) was supported by The National Research University Higher School of Economics Academic Fund Program in 2014/2015

Introduction

According to Sharp (1991), in terms of net returns to investors, active investment must be a negative sum game: if some active investors have positive alpha before costs, it is the expense of other active investors. This leads us to a important conclusion: funds with positive alpha are balanced by active funds with negative alpha.

Moreover, positive net alpha could be result of "luck" as it is below. The practical consequence is that investors cannot trust past performance of a "lucky" fund. Unlike skill, luck cannot be extrapolated. For US funds it seems to be impossible to select funds with superior future performance (e.g. Grinblatt and Titman, 1992; Hendricks et al., 1993; Brown and Goetzmann, 1997; Carhart, 1997; Wermers, 2003; Blake and Morey, 2000; Bollen and Busse, 2005; Mamaysky et al., 2007).

Distinguishing skill from luck is challenging. The data most commonly available are a time series of return for each fund. One of the approaches is to test persistence in mutual funds results. Addressing such a technique, we suppose that past winners continue to produce high results and losers continue to underperform (see, Grinblatt and Titman, 1992, Carhart, 1997). In other words, we suppose that luck can cause high returns only in the short-run. Such tests have a significant weakness. Short-term fund ranking are largely based on noise, a combination of short-term tests still seems to be based on noise.

Another commonly used methodology is a statistical test of whether an estimated alpha is significantly different from zero. The classical approach of inference is based on normality. However, we definitely should take into account features of managed-fund data. For a number of funds a time series of returns are short, and this makes classic time series asymptotics unreliable. There are other characteristics of data which makes inference complicated. Fund returns are mostly nonnormal, and funds vary in their volatility, autocorrelation, and skewness.

Recent studies apply the bootstrap procedure to address these statistical issues. Using a simulation of cross-sectional distribution of alpha (or another performance measure), it is possible to define whether the estimated alpha is significantly larger than the estimated alpha of a situation when true alpha is supposed to be zero. This approach supposes using long time series of individual fund returns and bootstrap simulations of return histories. Comparing actual fund alpha estimates to the bootstrap distribution makes it possible to infer alpha. An important advantage of bootstrap is that simulated fund returns have the properties of actual fund returns. The only difference is that we set true alpha to zero, as it is necessary for our purpose. Simulated returns are returns of funds with the same strategy but without any skills. Comparing these alpha estimates with actual alpha allows us to infer the existence of skilled managers.

Other authors (Baks et al.,2000, Jones and Shanken, 2005, Avramov and Wermers, 2006) use the Bayesian approach to avoid the weaknesses of classical inference. However, most papers suppose the bootstrap procedure provides appropriate results.

Results differ for different countries and markets (emerging and developed). Sometimes results even differ for the same countries. Kosowski et al. (2007) shows that the top 10% U.S. mutual fund alphas reflect skill. Cuthbertson et al. (2008) found, that for U.K. a relatively small number of top performing UK equity mutual funds demonstrate skill. Fama and French (2010) argue that these results are biased and use another boostrapping technique by jointly sampling fund (and explanatory) returns. Cuthberson and Nitzsche (2013) use the false discovery rate approach (FDR) to examine the skills of German funds. They find that at most 0.5% of funds have truly positive alpha-performance and about 27% have truly negative-alpha performance. Ayadi and Kryzanowski (2011) study Canadian bond funds and find that no fund possesses truly superior management skills. These studies show that for developed markets true alpha in net returns is negative for most active funds, even for funds with high positive alpha estimates for their histories. For emerging markets the number of studies is much less, and the results are different: Suh and Hong (2011) shows that a large proportion of Korean equity investment funds (60%) are estimated to be skilled funds.

Most of the previous studies focus on developed markets. Russ Wermers in his review suppose that "further research advances should be made for non-U.S. asset managers; some has been completed for non-U.S. mutual funds, but much more is necessary" (Wermers, 2011, p. 570). Skills examination of managers on emerging markets is the worthy goal because of market peculiarities (high volatility, low liquidity, low efficiency, etc) which influence the percentage of skilled managers. It is important to compare the results of emerging and developed markets in order to understand how the financial and associated institutional features of emerging markets influence the managers' skills.

This paper will examine Russian mutual funds. The asset management industry is a high growth industry in Russia. Assets under management (AUM) value has increased 93% over the past 10 years according to the Federal Financial Markets Service data. Such growth shows that typical issues on fund performance estimations are now topical in Russia.

Taking into consideration the results of Kacperczyk et. al. (2013) who show that managers' skill are time-varying and find evidence for stock picking in booms and for market timing in recessions, we will test the skill of mutual fund managers in different time periods. We will treat the 2004 – 2007 as a period of growth, 2008 – 2009 as a crisis period and 2010 – 2014 as a period of recovery.

Data description

We examined the daily returns of Russian mutual funds. The data was collected manually using mutual fund sites and using the InvestFunds database. Our final database contains 219 funds. We analysed only equity funds in order to make our results comparable with previous studies. The sample period is from January 2004 to January 2014, thought for a number of funds the returns series start later than 2004. The average number of observations is 1443 days.

For most funds (except 3) the distribution of returns is non-normal, according to the Jarque-Bera test. This is important for inference purposes, as we cannot rely on asymptotic-based tests.

The choice of benchmark is important. There are two benchmarks which are calculated by the two Russian stock exhanges: MICEX (Moscow Exchange) and RTSI (The Russian Trading System Index). Moscow Exchange is the largest exchange group in Russia, operating trading markets in equities, bonds, derivatives, the foreign exchange market, money markets and precious metals. The exchange was established in December 2011 by merging the Moscow Interbank Currency Exchange (MICEX) and the Russian Trading System Both organisations had been formed in the 1990s and were the leading Russian exchanges for two decades with their MICEX Index and the RTS Index (Moscow Exchange Official Site).

Table 1: Descriptive statistics of benchmarks

	MICEX	RTSI	MXRU
Minimum	-0.19	-0.18	-0.22
Maximum	0.29	0.23	0.27
Mean	0.00	0.00	0.00
Median	0.00	0.00	0.00
Stdev	0.02	0.02	0.02
Skewness	0.54	0.11	0.34
Kurtosis	19.74	16.11	20.51
N	2623	2623	2623

The MICEX Index was launched on September 22, 1997. It is calculated based on the prices of the 50 most liquid Russian stocks of the largest and dynamically developing Russian issuers with economic activities related to the main sectors of the Russian economy presented on the Exchange. This index is calculated in real time and denominated in rubles. The RTS Index was started on September 01, 1995. The RTSI is calculated based on the prices for the 30 most liquid Russian stocks listed on the Moscow Exchange. The index is calculated in real time and denominated in US dollars . Both indices are is capitalization-weighted composite indices (Moscow Exchange Official Site).

However, each index (MICEX and RTSI) has its disadvantages. MICEX and RTSI do not take dividend return into consideration, thought it is high for many popular Russian companies (LKOH, SBER, etc.). Moreover, some of the stocks included in these indexes are illiquid and are not available for private investors.

Taking this into account, the MSCI Russia (MXRU) was chosen as the best mutual fund benchmark. It takes into account the dividend return and has more strict requirements of liquidity for included stocks. However, MICEX and RTSI were also considered as most popular benchmarks in order to compare results for most popular and most suitable benchmarks.

Table 1 provides the summary statistics of benchmarks.

RTSI and MICEX looks very similar, but there are differences between them and MXRU. The minimum return for MXRU is lower and kurtosis is higher. This shows that the benchmark portfolio of stocks available for private investors (MXRU) is riskier than the generally accepted benchmark (MICEX or RTSI).

Methodology

In order to compare our results with the results for developed markets it is necessary to use the same methodology that the previous authors used. For that reason we will use Jensen's alpha as a performance indicator and bootstrap methodology to test skill versus luck.

Jensen's alpha (Jensen, 1968) is calculated as follows:

$$\alpha = r - (r_f + \beta \cdot (r_m - r_f)) \tag{1}$$

where r – mutual fund return, r_m – benchmark return, r_f – return of risk-free asset.

To estimate Jensen's alpha we need to estimate the following regression (the constant is this equation is Jensen's alpha):

$$r - r_f = \alpha + \beta \cdot (r_m - r_f) + \varepsilon \tag{2}$$

We do not use other pricing models like Fama-French or Carhart models, because Fama-French factors suppose the existence of a number of well-traded, liquid companies in each portfolio (small-cap, large-cap and so on). For the Russian stock market there will be from 7 to 10 such companies (despite the fact that there are approximately 2000 listed companies), so there is no sense in calculating these portfolio returns and, consequently, factors. We can use available US or European factors, but those stocks are not available for Russian investors. This is important since we use a pricing model as benchmark for mutual fund.

After the alpha estimation we need to ask whether alpha significantly differs from null. To answer this question, we need a proper alpha inference. In this setting, the main reason why the bootstrap is necessary for proper inference is the propensity of a mutual fund to exhibit a non-normally distributed return. These non-normalities arise for several reasons. First, the distribution of the shares in a mutual fund portfolio may be non-normal. Second, the market index (benchmark) may be non-normal, and co-skewness of the market and fund returns may be obtained. Further, fund returns exhibit varying levels of time-series autocorrelation.

Thus, normality may be a poor approximation in practice, even for a fairly large sample.

Bootstrapping can substantially improve on this approximation, as Bickel and Freedman (1984) and Hall (1988) show.

The chosen bootstrap procedure is based on the work of Kosowski el al. (2007). Here we provide a very brief explanation, the full description of bootstrap is available in the aforementioned paper.

1. For each fund we estimate the Jensen's alpha and save the residuals $\hat{\varepsilon}_t$.

2. We draw a sample with a replacement from the residuals (which were saved in the first step) $\hat{\varepsilon}_t$ and corresponding benchmark returns r_{mt}

3. Next we construct a time series for the pseudo returns, imposing the null hypothesis of zero true performance ($\alpha = 0$): $\hat{r} = 0 + r_{mt} \cdot \beta + \hat{\varepsilon}_t$.

4. The artificial returns have a true α that is zero by construction. When we regress these returns on the market index (benchmark) and estimate the Jensen's alpha of this artificial returns series. A positive estimated alpha may result, since that bootstrap may have drawn an abnormally high number of positive residuals, or, conversely, a negative alpha may result if an abnormally high number of negative residuals are drawn.

5. Next we repeat the steps described above across all funds $i = 1, \ldots, N$ for describing the cross-section of bootstrapped α. Repeating this for all bootstrap resampling simulations, $b = 1, \ldots, 1000$, we build the distributions of these cross-sectional draws of α and β.

6. Next we compare the actual Jensen's alpha from step *1* with the 2,5% and 97,5% quantiles of bootstrapped ("luck") distribution.

Empirical results

We divide our sample into three periods: before crisis (2004 –2007), crisis (2008 – 2010) and after crisis (2010-2014) in order to estimate managers' skills in different macroeconomics conditions (replication data is available on request).

Table 2 provides the summary statistics of estimated alphas across different benchmarks. Analyzing this table, we can conclude that the results for different benchmarks are similar. However, the mean alpha for MXRU is lower than for others. This means that it is is more difficult to outperform this benchmark. We suppose that underestimation of skill is less important than overestimation for an investor. For this reason we will consider MXRU as a best benchmark.

Table 2: Descriptive statistics of α with different benchmarks

	MXRU	MICEX	RTSI
	2004 – 2008		
Minimum	-0.07	-0.06	-0.06
Maximum	0.04	-0.00	0.00
Mean	-0.02	-0.02	-0.02
Stdev	0.02	0.01	0.01
N	219	219	219
	2008 – 2010		
Minimum	-0.05	-0.05	-0.05
Maximum	-0.02	-0.02	-0.01
Mean	-0.03	-0.03	-0.02
Stdev	0.01	0.01	0.01
N	219	219	219
	2010 – 2014		
Minimum	-0.06	-0.06	-0.06
Maximum	0.02	0.02	0.02
Mean	-0.02	-0.01	-0.01
Stdev	0.01	0.01	0.01
N	219	219	219

Figure 1 shows the densities of alpha and skill indicator in different time periods. The number of skilled managers differs from period to period. Table 3 provides the number of skilled managers.

The main results are listed below:

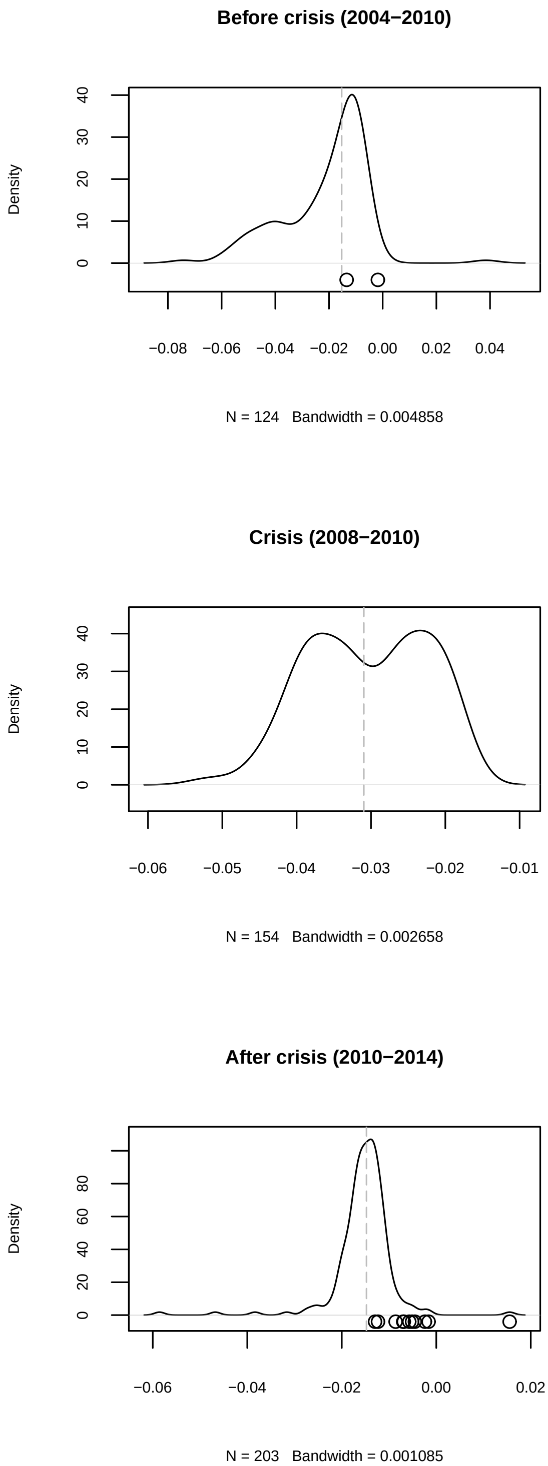

Figure 1: Alpha density and skills in different periods

The points under the density plot indicate the the skill corresponding to the alpha. Vertical grey line indicates zero.

Table 3: Number of skilled managers with different benchmarks

	MXRU	MICEX	RTSI
Before crisis (2004 – 2008)	1,62% (2)	1,62% (2)	2,42% (3)
Crisis (2008 – 2010)	0,00% (0)	0,00% (0)	0,00% (0)
After crisis (2010 – 2014)	5,42% (11)	4,55% (9)	4,55% (9)

- There is no manager who showed skill during the crisis period. This is consistent with results of the Kacperczyk et al. (2013) who showed that managers' skill is time-varying and find evidence for stock picking in booms and for market timing in recessions.
- All densities are skewed and left-tailed: the probability of getting an extremely low result is higher than the probability of extremely an high result.
- It is interesting that skilled funds are not characterized with the extremely high alpha. Apparently, the idiosyncratic variation in residuals for top-alpha funds is high, which showed that such a high alpha is the result of luck. This leads to an unexpected conclusion: an investor should avoid funds with a very high alpha.
- All skilled funds in our sample are positive-skilled funds. The is no manager who show negative results which cannot be interpreted as luck.
- The results differ across different benchmarks. In the after crisis period it is easier to outperform MXRU than other benchmarks (despite MXRU being the only which considers dividend returns). MXRU includes the most accessible stocks for private investors. It can be concluded that Russian mutual funds may earn abnormal alpha using stocks which are included in other less liquid indices. Such stocks may be not available for private investor (therefore they are not included in MXRU), but they are available for a mutual fund (as an institutional investor).

Cross-country comparison

Table 4 provides the proportion of skilled managers in different studies.

The number of skilled funds in Russia is very similar to developed markets, but differs from the Korean market. This is strange, because Russian market is supposed to be an

Table 4: Cross-country skill comparison

Paper	Sample	Skilled funds
Fama, French, 2010	USA	3%
Cuthbertson et al., 2008	The U.K.	5%
Kosowski et al., 2007	USA	0%
Ayadi and Kryzanowski, 2011	Canada	0%
Suh and Hong, 2011	Korea	60%
This study (whole sample)	Russia	5%

emerging and the results should be closer to Suh and Hong (2011).

The possible answer is benchmark. It is relatively easy for Russian funds to outperform local benchmarks. In all studies above, funds were compared with local benchmarks, which seems to be reasonable. Local benchmarks addresses local risks and local macroeconomics conditions. Still, thanks to internalization of stock markets, the transaction costs of investing in foreign markets are becoming less and less. This raises an interesting question about comparing mutual funds of different countries over same the benchmarks. However, choosing (or even constructing) such benchmarks would be challenging.

Conclusion

In this paper, we tested the Russian mutual fund managers' skill versus luck. We used the same methodology as Kosowski et al. (2007) and Fama, French (2010) in order to make our results comparable with previous studies focussing on developed markets.

The results of this research indicate that Russian mutual fund managers show a similar percentage of skill in comparison with developed markets. Nevertheless, this percentage is low, which supports the idea of Fama and French (2010) that there are some managers with enough skill to produce positive significant alpha, but their tracks are hidden in the aggregate results by the performance of managers with insufficient skill.

Our results differ from the results of Suh and Hong (2011) for the Korean market. We suppose that testing skill versus luck in emerging markets is a fruitful topic, because our results for emerging markets are similar to developed markets. It is important to find the causes of these differences and similarities of results for emerging and developed markets. This could induce some changes in institutional regulation of Russian (or other emerging) markets. For example, a new benchmark may be developed for cross-country comparison or self-comparison with a recommended benchmark could become obligatory.

The current investigation was limited by a relatively small sample size in terms of cross-section (thought the time series' length was adequate). Our results might not be transferable to other markets with a larger number of funds. The second limitation were the benchmarks: chosen benchmarks contained a relatively small number of stocks. However, this is problem of low liquidity most stocks on Russian market.

The main issue left unaddressed in this study is how to compare results for different markets. It is quite reasonable to compare local funds to local benchmarks. Still, it is unclear how to compare skills versus luck testing across different countries. We suppose that further research should be made for emerging markets asset managers to understand why results differs.

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This study (research grant No 14-01-0071) was supported by The National Research University Higher School of Economics Academic Fund Program in 2014/2015