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HIGHER SCHOOL OF ECONOMICS

Nikolai A. Manushkin

APPLICATION OF FAMA-FRENCH FIVE FACTOR MODEL ON THE RUSSIAN MARKET

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Nikolai A. Manushkin[1]

APPLICATION OF FAMA-FRENCH FIVE FACTOR MODEL ON THE RUSSIAN MARKET

This paper tests the applicability of various asset pricing models: Capital Pricing Model (CAPM), 3-factor and 5-factor Fama-French models to the Russian stock market, which has not been not well studied. We capture specific factors of this market, create several market portfolios, and use bootstrapped GRS test (Gibbons, Ross, & Shanken, 1989) for models' quality test. The empirical result shows that the 5-factor model fits the Russian market better than the other models, the value factor is redundant, and the size factor also loses its significance.

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[11] National Research University Higher School of Economics. E-mail: namanushkin@hse.ru

Introduction

The first asset pricing model, the Capital Asset Pricing Model (CAPM), was introduced by Sharpe (1964) and Lintner (1965) (Nobel Prize for Sharpe in 1990). However, CAPM was not ideal, and researchers continue to explore new patterns on the market. Fama and French (1993) suggested a 3-factor model. Basically, this model was an improvement of the CAPM model, but Fama and French included 2 additional factors, Size and Value. The high coefficient of determination and the high explanatory power of this model, along with the quality of the estimated parameters, allowed it to become one of the most popular tools for analyzing capital markets both in practice and academic research. In 2015, the same authors Fama and French provided the updated version of this model: the 5-factor model by adding two more factors Profitability and Investment. Today, the 5 factor model is widely used for practical working.

Even though this model is not a brand-new tool for the financial world, the research projects on this topic continue to develop. Researchers across the world try to find new evidence of the patterns for different markets. At the same time, there are few studies devoted to examining the Russian market. However, the Russian market is developing at an impressive pace and attracts many clients each year. Potentially, asset pricing models can help an investor in constructing a suitable and valuable portfolio.

The purpose of the paper is to find patterns that characterize the Russian market and choose the best fitted model. Thus, we apply different types of factor models for the market, using classical Fama-French sorted portfolios, to find out which model has better explanatory power for the Russian market.

The paper is organized as follows. Section II provides the literature review; Data and methodology are represented in section III; construction of factors and portfolios are demonstrated in this section; Section IV contains empirical results of the analysis; Finally, in section V, we present conclusions.

Literature Review

Sharpe (1964) uses the Portfolio Theory as the base to develop the CAPM. This model establishes a relationship between expected return and risk of a security or portfolio through beta-coefficient. However, the results of testing this model in practice were somewhat ambiguous. The premises on which the model is based are unrealistic. So, Ross (1976) develops the Arbitrage Pricing Theory (APT). The APT explains the expected return of securities as a linear function of various factors. The theory comes from a different perspective compared to CAPM mean- variance analysis. By that time, Banz (1981) found a new anomaly in the market. He demonstrated that small companies according to capitalization have larger risk premiums. Stattman (1980) shows evidence that the value factor also remains unexplained by CAPM.

Fama and French (1993), having relied on the logic and evidence provided by previous researchers, demonstrated the 3-factor Fama French model. The logic of the CAPM and APT models formed the basis of the 3-factor model. Fama and French also used size and value patterns for their model. As a result, the model had greater descriptive power. At the same time, the regression coefficients for the market portfolio were adjusted. However, the exposure to these three factors did not completely explain the expected returns of an asset or a portfolio. In 2004, Titman showed an investment factor, when conservative companies tend to have greater average excess return compared to aggressive stocks. Novy-Marx (2013) observed that profitable companies beat non-profitable companies by returns.

Fama and French (2015) released their well-known 5-factor model. In this model, they included market, size, value, investment, and profitability factors. This 5-factor model offers better results than the 3-factor model.

Currently, there are more than three hundred significant factors presented in authors' works (Harvey, Liu, & Zhu, 2015), while the number of potential factors is even greater. Cochrane (2011) described this situation as a “zoo of new factors,” highlighting their diversity and abundance. In response to this, Fama and French (2017) suggested that relying on economic theory is necessary the same way as it was done with CAPM, which means that even if the data shows evidence of some pattern, it does not mean that it is true and robust. Most likely this theory should be based on a rational economic agent and its behavior. Otherwise, the rationale may look unconvincing.

To test the efficiency of the models statistically, GRS statistics (Gibbons, Ross, & Shanken, 1989) has been proposed. The null hypothesis of this statistic is that all alphas of the regressions obtained when testing portfolios or assets are simultaneously equal to zero. Thus, if the intercept is not zero, this indicates the presence of the factors not included in the study model. However, according to Harvey and Liu (2021), the GRS test requires i.i.d normal assumption, which usually not the case for the market data and it is not efficient for a small sample. Therefore, it might be a threat for developing markets.

Nowadays, we can avoid some of the limitations by using bootstrapping. Kim and Choi (2017) used bootstrapping to determine the optimal significance levels in which Type I and Type II errors are avoided. Within the framework of this approach, the authors accept the null hypothesis when analyzing the Fama-French 3-factor model.

However, can Fama and French (2015a, 2015b, 2017) research findings on the US equity market be extended to other markets? Is there a need for continuous testing of individual markets? Bekaert and Harvey (2017) conclude that despite globalization, emerging markets remain only partially integrated into the global capital market and should be considered a distinct asset class. There are barriers that prevent the free movement of capital. Thus, it becomes necessary to test the model on an international market. However, researchers are faced with the problem of a lack of data in the stock markets of developing countries to conduct a proper quantitative analysis.

However, before moving to the research using emerging market data, it is worth noting the work of Fama and French (2017), which used data from 23 developed markets grouped into four regions: North America, Japan, Asia and Oceania, and Europe. Using this kind of aggregate data, the researchers tried to increase the diversification of the analyzed portfolios, which should lead to the refinement of the intercepts of the regressions. In this paper, the author used data for factor construction according to several markets of a region, and evaluated the portfolios by using data from one market. However, it can be concluded that the models better explain returns by using factors generated from local market data.

In addition, Leitea et al. (2018) confirmed the importance of using local factors in testing the models for emerging markets. The authors found that the 5-factor and 4-factor models tended to be better compared to the 3-factor model. The value factor is becoming redundant for the 5-factor model. Fama and French (2015b, 2020) made a similar conclusion regarding the value factor when testing the 5-factor model in the US stock market. Foyer (2018) showed that the size and investment factors lose their significance for considered developing markets. At the same time, the 5-factor model shows a better result compared to the 3-factor model.

Thus, we can note the lack of consistency in results on this topic for different markets. There is both evidence of persistence of premiums for the size and value factor, and evidence to the contrary. However, researchers have noted a greater descriptive power of the multifactor models compared to CAPM. Most authors use the same tools for the model selection: GRS test, adjusted coefficient of determination, and mean absolute value of intercepts.

Data and methodology

Data description

This paper uses data on Russian public companies whose ordinary shares are traded or were traded on the Russian stock market. All required company data was taken from the Bloomberg database and the Moscow exchange website. The analysis does not include preferred shares or depositary receipts. At the same time, there are observations on companies that have been delisted through the research period. This was made to control "survivorship bias", i.e., a problem that can arise when analyzing only existing companies.

The total sample includes 420 non-financial companies. The author excludes financial firms because they are in general highly leveraged, which is not normal for other types of companies, hence it can have an impact on research. The number of companies varies between 2005 − 2019 because of several reasons. Based on the uncertainty index (figure 1), we suppose that the time between 2005 – 2019 was relatively stable. Also, data availability is another factor. The Russian market represented by Moscow exchange is a developing market, therefore every year, the list of the companies may change, but should not have an impact on portfolio construction for our research. So, the overall available sample is sufficient for our purpose.

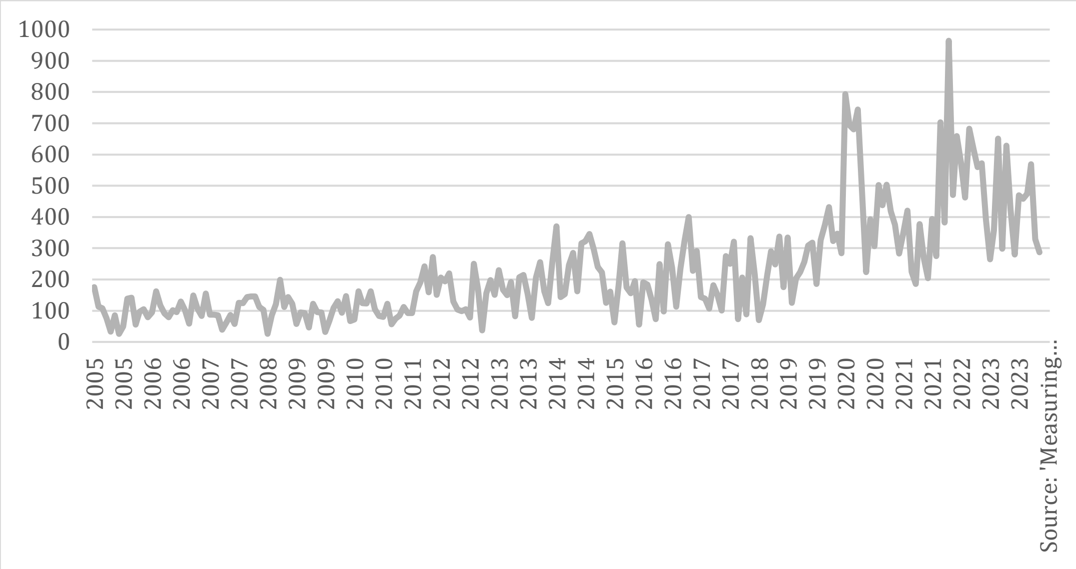

Figure 1. Policy Uncertainty Index

Models and statistical tests

To achieve the goal of this research, the current study evaluates several models: CAPM (1), 3-factor (2) and 5-factor Fama-French (3) models. The 4 factor models (3 factor Fama-French + CMA/RMW) are also tested. The procedure will consist in the sequential inclusion of factors from CAPM to the 5-factor model.

The Capital asset pricing model (CAPM) is given by

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + \varepsilon_{it} , \quad (1)$$

Where, R_{it} is return on asset/portfolio, R_{ft} is risk-free rate, which is chosen to be 10-yrs Russian government bonds yield; R_{mt} is the excess market return, β_i is market beta, and ε_{it} – stochastic error term.

The 3 Factor Fama-French model is given by

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_i SMB_t + h_i HML_t + \varepsilon_{it}, \quad (2)$$

SMB is the size factor calculated by subtraction of average monthly return on biggest companies from monthly return on smallest companies by capitalization. HML is the value factor, which is the average monthly return on companies with the highest B/M ratio subtracting average monthly return on companies with the lowest B/M.

The 5 Factor Fama-French model is

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_i SMB_t + h_i HML_t + c_i CMA_t + r_i RMW_t + \varepsilon_{it}, \quad (3)$$

In this case to market, size, and value factor we add two new factors, CMA and RMW. CMA stands for investment factors − average monthly return on conservative companies minus average monthly return on aggressive companies. RMW is the Profitability factor, i.e., average monthly return on robust (high operating profit subtract average monthly return on weak companies (low operating profit).

Comparison of the models, within the framework of the description of a separate portfolio, will be carried out according to the criteria used in the literature.

The first criterion is the adjusted coefficient of determination, which indicates how well the model explains variation over time in returns, i.e., the higher the indicator, the more variation in excess return is described and the better the model is.

The second one is the absolute value of the intercepts, and it explains variation across portfolios in average return. A smaller value of this indicator means the model is better, with factors capturing more excess return of the asset.

The third criterion is the test of the efficiency of the given portfolio − GRS-test, provided by Gibbons, Ross, and Shanken (1989). The null hypothesis of this test is that all intercepts of an asset pricing model are jointly equal to 0. Thus, in this case, we do not reject the null hypothesis. It is possible to apply this test to any type of asset pricing model to test the alpha-intercepts. The GRS-test statistic is given in the following way:

$$GRS = \frac{T(T-N-K)}{N(T-K-1)} \times \frac{\widehat{\alpha}`\widehat{\Sigma}^{-1}\widehat{\alpha}}{1+\widehat{\mu}`\widehat{\Omega}^{-1}\widehat{\mu}}, \quad (4)$$

Where, α is the vector of intercepts, Σ is the residual covariance matrix μ is vector of factors' average value Ω is covariance matrix of factors T is time length N is the number of assets (portfolios); and K is the number of factors.

Then, by using F-statistics, we can compare GRS results with it and decide whether we reject the null-hypothesis. If the model describes the excess return variation, then, consequently, the intercepts of the regressions should be equal to zero. The GRS test takes a low value in this case, which indicates a high probability of accepting the null hypothesis.

However, the GRS test is based on independent and identically distributed random variables (i.i.d) normal assumption since data is usually not normally distributed the test suffers from statistical problems. Thus, in this research, the approach of Kim and Choi (2017) will be used. An optimal level of significance and critical value will be found by bootstrapping method.

An optimal level of significance is the level at which the probability of a type I error (rejection of a correct hypothesis) is in "equilibrium" with the probability of a type II error (non-rejection of a false hypothesis), which is used directly to calculate the power of the test: it is necessary to subtract the probability of error from the unity of the second kind to obtain the power of the test.

If calculated GRS-statistics is greater than an optimal bootstrapping critical value, then we reject the null-hypothesis. Also, we have to control the probability of type II error. If it is too high, we increase chances to get false acceptance of null-hypothesis.

To determine the importance of including a particular factor in the model, we use four factors in regressions to explain average returns on the fifth. It is used to test how much a single factor can be explained by others. Thus, the following models need to be tested:

$$(R_{mt} - R_{ft}) = \alpha_i + s_i SMB_t + h_i HML_t + c_i CMA_t + r_i RMW_t \, , \tag{5}$$

$$s_i SMB_t = \alpha_i + (R_{mt} - R_{ft}) + h_i HML_t + c_i CMA_t + r_i RMW_t \quad , \tag{6}$$

$$h_i HML_t = \alpha_i + + s_i SMB_t + \beta_i (R_{mt} - R_{ft}) + c_i CMA_t + r_i RMW_t \, , \tag{7}$$

$$c_i CMA_t = \alpha_i + s_i SMB_t + h_i HML_t + \beta_i (R_{mt} - R_{ft}) + r_i RMW_t \tag{8}$$

$$r_i RMW_t = \alpha_i + s_i SMB_t + h_i HML_t + c_i CMA_t + \beta_i (R_{mt} - R_{ft}) \, , \tag{9}$$

The conclusion about the importance of a factor is made based on the intercept of equations above. If intercepts are significant, then other factors cannot fully describe the variation of the analyzed factor. Otherwise, the factor is redundant.

Construction of the factors

In this research paper, the asset pricing factors are calculated following Fama and French (2015b), with the intuition that there must be a close link between the firms' characteristics and their expected return. Factors were constructed based on a 2x2 sort on Size and B/M, Size and OP, Size and Investment, as demonstrated in table 1.

The fiscal year coincides with the calendar year, so due to data characteristics, most and necessary data become available at the end of June. Such information as book value and operating profit margin are available only in annual format. So, at the end of June, stocks are allocated in portfolios according to their characteristics. Excess return is captured in a monthly format.

All the available stocks are divided into two size groups: small and big, according to their market capitalization, and the breakpoint is MOEX median, after which those stocks are chosen independently by value, profitability, and investment factors, and allocated to the portfolios. The portfolios we construct are as following: Small and High (Size-Value); Small and Low (Size-Value); Small and Robust (Size-Profitability); Small and Weak (Size-Profitability); Small and Conservative (Size-Investment); Small and Aggressive (Size-Investment); Big and High (Size-Value); Big and Low (Size-Value); Big and Robust (Size-Profitability); Big and Weak (Size-Profitability); Big and Conservative (Size-Investment); Big and Aggressive (Size-Investment).

Table 1. Construction of Size, B/M, profitability, and investment factors

Sort	Breakpoints	Factors and their components
2x2 sorts on	Size: MOEX median	SMB = (SH +SL + SR + SW + SC + SA)/6 – (BH + BL + BR + BW + BC +BA)/6
Size and B/M	B/M: MOEX median	HML = (SH + BH)/2 – (SL + BL)/2 = [(SH – SL) + (BH – BL)]/2
Size and OP	OP: median	RMW = (SR + BR)/2 – (SW + BW)/2 = [(SR – SW) + (BR – BW)]/2
Size and Inv	Inv: median	CMA = (SC + BC)/2 – (SA + BA)/2 = [(SC – SA) + (BC – SA)]/2

Further, we construct the Small / Big, High / Low, Robust / Weak and Conservative / Aggressive factors as described in table 1 and characteristics in our sample’s factors, represented in table 2.

According to information in table 2, HML, RMW, and CMA, on average, have a positive return and similar deviations from the mean. However, Market and SMB factors have a negative return. For SMB it is less than 1%. Market factor has a negative almost 4% return, because of the high level of the risk-free rate. Like developed markets, emerging markets are usually characterized by a high risk free- rate.

Table 3 demonstrates correlation matrix for the entire period. Significant level of correlation in general does not appear, the highest 38% correlation is observed only between RMW and HML factors. Other than that, there is no correlation between factors.

For the Russian market portfolios, the highest correlation is between HML and RMW. It shows that companies with a high book-to-market ratio, in general, are more stable and profitable. This result may not come as a surprise given that usually value stocks, with high book to market value, because of their robustness to market fluctuations. Also, it might be due to Russian market features, since historically, the Russian economy is mostly based on commodities, and companies in this sector usually have a high degree of B/M ratio. Graham explained this correlation in his book "*Securities Analysis"* where he talks about deep value investing − investing in firms with a book to market ratio greater than 2 in the aftermath of the 1929 crisis delivered high returns.

Table 2. Summary statistics for monthly factor percent return

	Rm-Rf	SMB	HML	RMW	CMA
Mean	-0.039	-0.010	0.020	0.035	0.017
St. Deviation	0.072	0.126	0.151	0.168	0.152
Max	0.203	0.352	0.256	0.184	0.190
Median	0.017	-0.007	0.007	0.020	0.012
Min	-0.287	-0.243	-0.192	-0.205	-0.158

Table 3. Correlation matrix between factors

	Rm-Rf	SMB	HML	RMW	CMA
Rm-Rf	1.00	-0.120	0.130	0.134	-0.019
SMB	-0.120	1.00	0.037	0.200	-0.061
HML	0.130	0.037	1.00	0.382	0.007
RMW	0.134	0.200	0.382	1.00	-0.247
CMA	-0.019	-0.061	0.007	-0.247	1.00

Another interesting result can be extracted from the correlation between the size and profitability factors. The size factor is only positively correlated with the profitability factor, which reinforces the idea that small and medium sized firms are generally the most profitable.

Finally, the correlation between profitability and investment is negative, which would seem intuitive given that according to this result, the most profitable firms tend to be more aggressive when investing. However, this result may suffer from what is commonly called survivorship bias: of all the firms that engage in aggressive investment strategies, only those that manage to be profitable.

Overall, the correlations among the factors are not too high, except for RMW and HML. For example, the results observed by Fama and French (2015b) show that the HML was highly redundant when the other risk factors were incorporated. According to them, "The average HML return is captured by the exposures of HML to other factors. Thus, in the 5-factor model, HML is redundant for describing average returns, at least in U.S. data for 1963−2013". (Fama & French 2015b). Just looking at the correlation matrix, we cannot be sure whether the value factor is redundant or not, so further tests will be carried out.

Construction of the market portfolios

The classical approach to portfolio construction is used in this paper, following Fama and French research. However, because of limited data availability compared to the original research, we decided to compute 16 portfolios of each type instead of 25.

We divide all the market data, to describe the Russian market as precisely as possible. In total, 48 portfolios have been used: 16 based on size and value, 16 on size and profitability, and 16 on size and investment. For a company to be identified in a particular portfolio, a combination of three conditions is necessary:

It has observations of the Operating Profitability which reflects the residual income that remains after accounting for all the costs of doing business.

Book value − Book value is a company's equity value as reported in its financial statements. It is used for forming value and investment factors.

Market Value − Market capitalization of a company according to the Moscow exchange.

In tables 4, 5, and 6, all the returns are represented in a matrix form, from top to bottom companies captured according to their market size. Next, from left to right, changes in table 4 are reflected according to book to market ratio. Finally, in table 5, it is done according to operating profit margin, and in table 6, according to the investment factor.

In table 4, we can capture evidence of the size effect, which is historically related to the period during 2005−2019 for the Russian market. The smallest companies tend to have a higher excess return compared to the biggest companies. However, the value effect is observed only for small companies.

For Size-OP portfolios, we again find evidence of the Size effect, where smaller companies have a higher average excess return. The profitability effect also appears. In general, profitable companies have the excess return twice as high when compared to the weak group.

Table 4. Summary statistics average excess return of 16 Size-B/M portfolios

	Size-B/M			
	Low	2	3	High
Small	0.047	0.054	0.023	0.075
2	0.000	0.015	0.036	0.028
3	0.080	0.018	0.041	0.001
Big	0.026	0.016	0.028	0.019

Table 5. Summary statistics average excess return of 16 Size-OP portfolios

	Size-OP			
	Weak	2	3	Robust
Small	0.055	0.050	0.050	0.105
2	-0.018	0.069	0.008	0.045
3	0.009	0.013	0.008	0.015
Big	0.031	0.028	0.016	0.027

Table 6. Summary statistics average excess return of 16 Size-B/M portfolios

	Size-Inv			
	Conservative	2	3	Aggressive
Small	0.045	0.091	0.047	0.047
2	0.003	0.043	0.048	-0.003
3	0.027	-0.001	0.020	0.016
Big	0.020	0.018	0.038	0.013

Based on the results in table 6 the size effect was captured. Also as expected conservative companies have higher return compare to aggressive.

To sum up, the results of the summary statistics suggest that, at this stage of the research, several important patterns were observed: size, profitability, and investment. However, we propose that the value factor is not obvious. Since the available data demonstrate the existence of stable patterns, we will conduct further statistical research to confirm or reject these findings. The results of the empirical analysis are contained in Section IV.

Empirical results

To make the research comprehensive, we decided to add factors sequentially. Three most important models in asset pricing are used in the paper, according to their historical appearance: CAPM, Fama-French 3-factor model, Fama-French 5-factor model.

We use excess return on each portfolio, which we constructed in section IV, V, as a depended variable. In general, any type of asset/portfolio can be selected as a dependent variable in Fama-French regression for analysis, but we are following Fama-French approach in this section.

Results of the CAPM, Fama-French 3-factor, and Fama-French 5-factor are presented in this section. Following parameters are examined: 1. Average intercepts (α), this represents the average intercepts across the models, the best model is the one in which the least unexplained part of the excess return is observed. 1. Adjusted R^2, the average of adjusted coefficient of determination, showing the descriptive power of the model. The higher the indicator, the more variation in excess return is described by the model, making it a better model. 3. GRS Test Statistic (Gibbons Ross and Shanken), the null hypothesis of this test is that all alphas of the regressions obtained when testing portfolios or assets are simultaneously equal to zero. If test statistics exceed a critical value, we have to reject null-hypothesis, which is undesirable. GRS-p is used to denote the p-value of the GRS statistics, and Critical value stands for the critical value which is computed based on the bootstrap method, proposed by Kim and Choi (2017). Statistical test power is calculated by subtracting a probability of type II error from 1. Type II error probability is the probability of failing to reject a false null hypothesis, which states for the power of the test.

The bootstrap method is conducted using a built-in function in the GRS. test package in R, with a set value of the number of repetitions set to the three thousand. Increasing the number of repetitions does not significantly change the GRS test statistics, suggesting that three thousand is an optimal level. The function "GRS.optimalboot" allows to evaluate the optimal levels of significance and power of the test.

All the tests and regressions are demonstrated in Tables 7−9, which display the portfolios for companies categorized by different characteristics: size and value, size and profitability, size and investment pattern.

Size-B/M portfolios

The first portfolios are the Size-Value based; Table 8 demonstrates the average results of asset pricing models' performance. Figure 1 represents optimal level of significance of the GRS test of the 5-factor model, which shows that the power of the test does not exceed 90% level.

Table 8. 16 value-weighted Size-B/M portfolio

	$\underline{a}$	$\underline{R^2}$	GRS	GRS - p	Critical value (bootstrap)	Statistical test power
CAPM	0.1168	0.3317	5.8972	4.698e-10	5.718	0.931
3 FF	0.1015	0.4457	6.0689	2.387e-10	5.761	0.938
3FF+ RMW	0.1018	0.4489	5.8512	0.0008	5.864	0.915
3 FF + CMA	0.0332	0.4853	5.5412	0.6368	5.959	0.895
5 FF	0.0344	0.5515	5.2412	9.268e-09	5.211	0.927

Table 9. 16 value-weighted Size-OP portfolios

	$\underline{a}$	$\underline{R^2}$	GRS	GRS - p	Critical value (bootstrap)	Statistical test power
CAPM	0.0586	0.330	7.3998	8.228e-13	7.2622	0.890
3 FF	0.0505	0.314	6.9793	5.1006e-12	6.6930	0.910
3FF + RMW	0.0315	0.351	6.4818	5.1755e-5	5.7541	0.928
3FF +CMA	0.0174	0.450	7.4717	5.47111-e3	6.8548	0.935
5 FF	0.0263	0.521	6.0552	2.7083e-10	5.5988	0.934

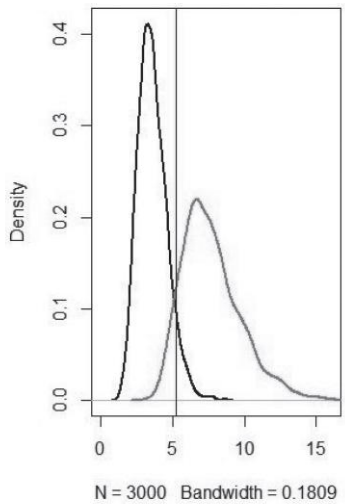

Figure 2. Density Functions Under H0 and H1 for 5 FF

According to the results represented in Table 8, the 5-factor Fama-French model demonstrates the best performance. The intercept tends toward zero as we add more factors, implying that the 5-factor model captures and explains the return on size-value portfolios much better compared to other models, accounting for about 55%. The coefficients of determination further support previous conclusions. However, the null hypothesis of the GRS test must be rejected for the CAPM, 3-factor Fama-French, and 5-factor Fama-French models, as none of the models' GRS statistics are smaller than the corresponding critical values. Hence, we can reject the null hypothesis that alphas are jointly equal to 0 for these models. Surprisingly, the 4-factor model could be accepted by the GRS test, suggesting that statistically, 4-factor models may be more sufficient. For the Fama-French 5-factor model, we almost did not reject the null hypothesis. Even if we slightly change the critical value, we can suppose that the model passed the GRS test successfully. However, it's important to understand that by doing so, we decrease the power of the test. Overall, the 5-factor model demonstrates the best result.

Size-OP portfolios

Another set of portfolios is based on size and profitability, with the corresponding results of the testing are demonstrated in Table 9, which shows similar results for size-profitability portfolios. By examining the average intercept and adjusted coefficient of determination we can suggest that for this type of portfolios, the 5-factor model is the best choice, despite the fact models still rejected by GRS statistics. At the same time 4-factor model (3FF + CMA) demonstrates the best result in terms of intercept. However, we encounter a situation when none of the models can be accepted by the GRS test.

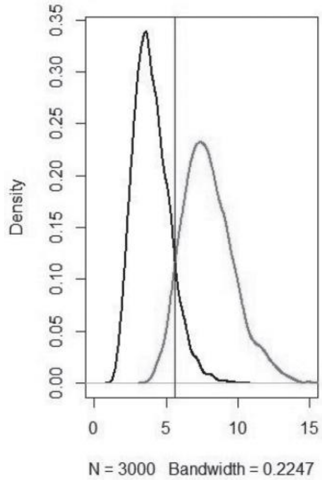

Figure 3. Density Functions Under H0 and H1 for 5 FF

Size-Invest portfolios

Table 10 confirms consistent findings, indicating that the 5-factor model is the best for explaining excess return on portfolios, it has the biggest adjusted coefficient of determination nearly 57%. However, unlike other portfolios, this test fails to reject the null-hypothesis of the test, which suggests that all alphas on our models are jointly equal to 0. Additionally, the probability of non-rejection of a false null-hypothesis is around 13% for each model, which is significant.

In conclusion based on results of these models, it can be suggested that the 5-factor Fama-French model is generally the most effective way to capture excess return on the Russian market, according to the results for these models. average alpha intercepts and adjusted coefficient of determination. In general, as additional variables are included, alphas tend to approach zero, and most models did not pass the GRS test; nevertheless, they were close to doing so.

Table 10. 16 value-weighted Size-Inv portfolios

	$\underline{a}$	$\underline{R^2}$	GRS	GRS - p	Critical value bootstrapping	Statistical test power
CAPM	0.0472	0.3135	3.9629	2.650e-06	4.0378	0.89
3FF	0.0438	0.3867	3.5652	1.658e-05	3.6860	0.861
3FF + RMW	0.0385	0.4937	3.8527	0.0042	3.5695	0.891
3FF + CMA	0.0318	0.4113	3.0155	0.0064	4.0158	0.915
5FF	0.0239	0.5699	2.7538	0.0064	2.9968	0.848

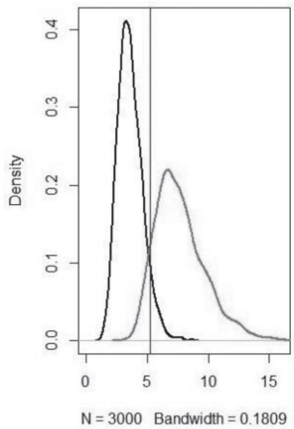

Figure 4. Density Functions Under H0 and H1 for 5 FF

Compared to Fama-French original research on the US market, the factors do not appear to have significant explanatory power. Considering the adjusted coefficient of determination, it is notably smaller in comparison to Fama and French findings. Aside from this distinction, the models and statistics give similar results. With the inclusion of more factors, the alpha tends towards zero, which is a good sign, suggesting that these factors have good descriptive power. Therefore, for further research, some additional factors might be added.

Conclusion

Asset pricing is an important and relevant area of study, particularly for emerging markets. Recently, there has been a sharp rise of amount private investors participating in the Russian stock market. Indicating a growing interest among individuals not only in preserving their capital but also in seeking for its growth. This is also facilitated by the government, introducing individual investment accounts (IIA), which allow one to receive tax benefits if certain conditions are met. One of these conditions is the term for the placement of funds, which prompts investors to make a more deliberate decision on the assets to be acquired. The pricing models under consideration can serve as an excellent tool for analyzing the expected return. It is available not only for the institutions, but also for individual investors.

The main purpose of this research was to test multifactor Fama-French models on the Russian stock market. Additionally, a novel approach was employed proposed by Kim and Choi (1986) to determine the optimal level of significance for the GRS test.

Based on the results of testing multifactor models, we can conclude that the 5-factor model, encompassing all the mentioned factors, best describes excess returns. However, it appears that the HML factor seems redundant. Additionally, the analysis suggests that the size factor (SMB) might be losing its significance according to the regressions. However, simple exclusion of the factor usually does not improve the quality of the model.

The research has several limitations and possible ways of further development. First, the definition of the market factor. In this study, the profitability of the Moscow Exchange Index was used as a proxy for the market portfolio. In some studies, researchers calculating the return of the market portfolio by averaging the returns of all stocks (Foye, 2018), this could be explored for a more comprehensive understanding.

Second, the filtering procedure by removing illiquid assets. However, in this case we can face the problem of lack of data, hence can get a bias in the results due to the loss of information. However, it might be worth testing the liquidity factor, which is also tested in emerging markets (Lalwani & Chakraborty, 2019), by testing the stock for extreme yields not relative to others, but relative to their own. Perhaps some outliers can be smoothed out, which can have a positive effect on data.

Third, the choice of percentiles used to divide stocks into portfolios presents a notable consideration. In this work, the conventional approach of dividing companies was applied as a starting point for further searches. Perhaps filling portfolios in some other way can improve the results, although some studies have shown resistance to both periods of portfolio rebalancing and changes in percentiles (Waszczuk, 2014).

Fourth, the main emphasis of the analysis was shifted towards the study of the performance of models from the standpoint of the generated alpha terms (intercepts). This parameter not only reflects the unexplained excess return of portfolios but also indicates their descriptive power. However, it is also necessary to analyze the models in terms of the remaining parameters of the regression: their signs and significance.

In general results of the findings are consistent. Fama-French 5 factor return is the most sufficient model compare to CAPM, 3 and 4 factor models. By using it we can explain on average $50\% - 60\%$ of the expected return.

Overall, the findings demonstrate consistency in the results. The Fama-French 5-factor model is the most robust compared to the CAPM, 3-factor, and 4-factor models. Utilizing it allows for the explanation of approximately 50% to 60% of the expected return on average.

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