“An empirical investigation of the Fama-French five-factor model”

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AN EMPIRICAL INVESTIGATION OF THE FAMA-FRENCH FIVE-FACTOR MODEL

Abstract

The article deals with evaluating the securities portfolios in the process of transition from the one-factor CAPM model to the Fama-French five-factor model (FF5F). It identifies the advantages of the latter and discusses the controversial issues regarding its use by portfolio investors in different countries, given the anomalies inherent in asset pricing. Besides, the peculiarities of the statistical stratification method used in the FF5F model to group stock portfolios are revealed, and attention is drawn to some of the debating points of the five-factor model. The proposals have been formulated, which offer broader avenues for taking advantage of the FF5F model and increase the validity of the portfolio analysis results. The article also gives recommendations on modifying the approaches to analyzing small-size portfolios versus big-size portfolios based on partial changes in RMW and CMA factors, threshold proportions, and the use of STARR for asymmetric portfolios. The study substantiates the use of these approaches in testing the Fama-French five-factor model with portfolios composed of blue chips.

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INTRODUCTION

During 2014–2019, the overall situation on the global stock market had a positive trend in terms of increasing key S&P 500, NASDAQ, and DJI stock indices by 57%, 99%, and 61%, respectively. This has inspired active investors to find the most effective securities portfolio management model. The change in investment expectations partly influenced the structure of the diversified portfolio, though its share fraction remains stable high.

Improvements to portfolio analysis tools have triggered controversy over the use of models that can more accurately justify changes in profitability and explain anomalies in asset pricing processes influenced by various factors. The presence of price anomalies may be due to either market failure or incorrect specification of previous models, in particular, CAPM.

Having investigated the use of the CAPM model, Fama and French (2014) found out that, on average, 70% of the expected return on a diversified portfolio can be explained by the value of the β coefficient, and 30% of the change in yield is attributable to other factors such as the company's capitalization, its undervaluation, profitability and investment rate. These factors were later reflected in the three- and five-factor Fama-French models.

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Fama and French approaches, which can explain the portfolio return adjusted for price anomalies, are rapidly growing in popularity. Over the past years, various aspects of using this model by portfolio investors have been discussed. Given the peculiarities of asset pricing processes in fragile economies in the context of increased volatility, low liquidity, and deviations from normal distribution, there is a need to continue testing this model to make it more efficient in justifying portfolio yield.

1. LITERATURE REVIEW

Asset portfolio optimization is a multifaceted problem in terms of finding a compromise between risk and return. According to Basu (1977), Banz (1981), Haugen and Baker (1996), in search for an adequate model, it is difficult to leave out the controversy over the efficient market hypothesis given the manifestations of price anomalies. Thus, Banz (1981) found a size effect, drawing attention to the negative relationship between return on equity and the firms' equity value. Basu (1977) proved that the expected return on equity with higher E/R values exceeds the values calculated based on CAPM. The emergence of various price anomalies seems to reveal major irregularities in the efficient market hypothesis.

Is this hypothesis confirmed in the context of contradictory empirical data, especially as applied to underdeveloped markets? Darushin, Lvova, Ivanov, and Voronova (2016), based on the test results of the main stock indices and the Russian Federation stock market shares in 2009–2016, proved that such a market remains weak and efficient even in unfavorable conditions. However, financial depth expansion, an increase in budgetary dominance, and volume of government securities transactions create new anomalies in the underdeveloped economies (Ivanov et al., 2019; Mishchenko, 2019).

Fama and French (1993, 1995, 1998, 2002, 2014–2017) theoretically substantiated and consistently developed the stock anomaly theory. They created a methodological basis for the research and formulating the proposals. Carhart (1997) elaborated on the three-factor Fama-French model by proposing a four-factor model (FFC4M); he added a WML (Winners Minus Losers) parameter – a momentum factor – to explain differences in return on equity based on the momentum effect. This model has not, however, become widespread among practitioners.

Zaremba and Czapkiewicz (2017) made a comparative analysis of CAPM, FFC4M, FF3F, and FF5F models and concluded that the FF5F model better explained portfolio returns given the current anomalies. The empirical evaluation of the FF5F model was taken by Ozkan (2018), Racicot, Rentz, and Théoret (2018), Qi (2017), Guo, W. Zhang, Y. Zhang, and H. Zhang (2017), Chiah, Chai, Zhong, and Li (2016), Huynh (2018), Paliienko (2019), and others. Thus, Ozkan (2018) confirmed the reliability of the model based on the Istanbul Stock Exchange (ISE) testing. Chiah et al. (2016) highlighted the benefits of using the FF5F model to explore pricing processes on the Australian stock market. Huynh (2018) used the FF5F model to explain the anomalies of asset pricing on the Australian market. Qi (2017) presented positive findings on using the model on the Chinese equity market, while Hapsari and Wasistha (2018) provided positive conclusions for the Indonesian Stock Exchange. Racicot, Rentz, and Théoret (2018) examined the use of an extended five-factor model for hedge fund portfolios.

However, discussions about the use of this model are still ongoing. Thus, Hapsari and Wasistha (2018) call for the need to modify the yield variables. According to Racicot, Rentz, and Théoret (2018), market risk remains the only significant factor. Dutta (2019) is skeptical about the ability of the FF5F model to detect long-term anomalies. According to Huynh (2018), three-factor and five-factor models did not pass the GRS test (Gibbons, Ross, and Shanken's test); this indicates that the search for the best asset pricing model is not yet complete. It should be noted that not only investors but also central banks, as active participants in the financial market in countries such as Ukraine, are beginning to claim compensation for additional risks (Mishchenko et al., 2016; Ivanov et al., 2015); this can put additional pressure on investors, enhancing market volatility, and make it more difficult to identify the relationship between portfolio returns and systematic kurtosis.

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2. DATA AND METHODS

In 1993, after continuous research, Fama and French proposed the three-factor model, which is as follows (Fama & French, 1993):

$$R_{it} - R_{Ft} = a_i + b_i\left(R_{Mt} - R_{Ft}\right) + \\ + s_i SMB_t + h_i HML_t + e_{it}, \tag{1}$$

where R_{it} – the return on security or portfolio i for period t, R_{Ft} – the risk-free return, R_{Mt} – the return on the value-weighted (VW) market portfolio, SMB_t (small minus big) – the return on a diversified portfolio of small stocks minus the return on a diversified portfolio of big stocks, HML_t (high minus low) – the difference between the returns on diversified portfolios of high and low B/M stocks, HML – a premium for the under- or overvaluation of a company; and e_{it} – zero-mean residual.

The combination of RMW_t and CMA_t, which consider differences in company assets in terms of their profitability and investment rate, has transformed the three-factor model into the five-factor model (Fama & French, 2015), which has formed the basis for the calculations.

The Fama-French five-factor model (FF5F model) is as follows:

$$R_{it} - R_{Ft} = a_i + b_i\left(R_{Mt} - R_{Ft}\right) + \\ + s_i SMB_t + h_i HML_t + r_i RMW_t + \\ + c_i CMA_t + e_{it}, \tag{2}$$

where RMW_t (robust minus weak) – the difference between the returns on diversified portfolios of stocks with robust and weak profitability, CMA_t (conservative minus aggressive) – the difference between the returns on diversified portfolios of the stocks of low and high investment firms, which Fama and French call conservative and aggressive.

All listed and traded stocks on the NYSE, AMEX, and NASDAQ were tested following the Fama and French approach. It has been empirically proven that a five-factor model can be applied to stocks with different risk-return profiles; besides, certain market anomalies that arise in the stock market were explained (Fama & French, 2014). However, this approach is related to implementing one of the strategies in portfolio management, namely, benchmark replication, when an investor forms a portfolio that is similar to a stock index, such as S&P500, or the index of an individual exchange-traded fund (ETF). Currently, only 38% of index-tracking ETFs use a benchmark replication strategy, while 41% of funds employ stratified sampling, which is the highest indicator among the strategies (CFA Institute, 2019). Note that an index portfolio is one of the most common forms of passive portfolio management.

The unique way of grouping stocks into portfolios, which is a type of the stratification method used in portfolio management to maximize the profitability of each portfolio while minimizing the variance of return and risk, is a special aspect of the five-factor model.

Stratification is a statistical technique for sampling events from the general set by dividing these events into individual subgroups according to factors or specific distribution characteristics. This method allows forming weighted average portfolios according to five factors and quantiles within the portfolio, which relate to an individual factor.

For example, for the size distribution according to the profitability factor, one can obtain six weighted average portfolios or six subgroups:

- three small-size portfolios: small-robust, small-neutral, and small-weak; and
- three big-size portfolios: big-robust, big-neutral, and big-weak.

In the FF5F model, the quantiles were 30% and 70%, so the shares were divided into three subgroups according to each factor. This 30% and 70% quantile share distribution affects kurtosis, i.e., extremums in tailed-risks distribution. This results in asymmetric data distribution and affects yield distributions skewness. It should be noted that this method of grouping stocks into portfolios according to the Fama and French (2014) approach is not based on linear or quadratic programming but appears as a modification of classical stratification.

The Fama and French method is specific in that it uses three stages of grouping:

1) the distribution of companies' shares into Big-Size and Small-Size according to Market Capitalization;

2) the distribution of shares within Big-Size and Small-Size portfolios using five factors; and

3) ranking shares into individual quantiles within six portfolios according to the Size factor and the intersection with each of five factors.

The Fama-French method allows the portfolio creation where the risk-return profiles of companies will be as similar as possible. Moreover, the application of this method is partly based on a modified stable Lévy distribution model, the truncated Lévy flight (TLF) (Darushin, Lvova, Ivanov, & Voronova, 2016, p. 24). The infinite variance of a stable Lévy distribution model greatly complicates risk assessment and limits the practical implementation of a stable Lévy distribution itself. However, one can parametrically control skewness and kurtosis, using a multivariate version of the TLF model, that is, cut off the extremums of the "distribution tails." Fama and French use this feature during the three stages of grouping.

The consistent implementation of these stages allows forming portfolios with far lesser kurtosis. Therefore, stocks with extreme yield changes will be in the same portfolio with the same stocks (small-size). Meanwhile, an opportunity arises to form a portfolio of companies that are very similar in the following characteristics: operating profitability, change in total assets, and book to market value ratio.

Thus, within each portfolio, kurtosis is cut off, and skewness takes a clearer single direction. Therefore, this type of stratification maximizes portfolio returns and minimizes the variance of returns due to the existence of individual data samples for six weighted average portfolios.

This approach has the following advantages:

- reducing the sampling error and decreasing the portfolio return variance;

- ability to include the same asset in portfolios with different characteristics (according to five factors and quantiles of grouping within each portfolio);

- profit maximization and risk minimization for each portfolio.

The disadvantages of the approach include the following:

- the potential for the Simpson paradox, when there is a certain trend, or there is a statistical data dependence within each subgroup. However, this trend disappears or becomes the opposite when combining subgroups into a single group;

- the dependence of stratification results on the number of shares within each portfolio and the successful grouping factors selected;

- the possibility of misrepresentation because the most volatile stocks may have small variance when forming an artificially selected portfolio with the required average value of return.

Without infringing the ingenuity of the Fama and French approaches embodied in the FF5F model, this study has formulated proposals that extend the potential for taking advantage of methodological approaches when applying the FF5F model and increase the validity of the portfolio analysis results. Table 1 presents changes in approaches when using the FF5F model.

The reason for choosing blue chip companies is that the market must be efficient to apply the FF5F model. Given the underdevelopment of the Ukrainian stock market and the predominance of government stock transactions on it, the portfolio was composed of shares of non-resident companies. US companies, whose stock price reflects all available information completely and almost instantly, are the closest to an effective market.

Market cap-based share allocation across portfolios using a threshold is proposed to be set at the level of 40% for the Big-size portfolio and, accordingly, 60% for the small-size portfolio. The FF5F model applies a 50% to 50% distribution, given a

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Table 1. Changes in approaches when using the FF5F model

Source: Developed by the authors.

Object	The FF5F model-based approach	Modified approach	Focus
Number of stocks in the portfolio	Use of stock information with many shares and optimal factor-based allocation	Using top 15 blue chips and building micro-portfolios with the asymmetric number of shares (6 and 9)	Possibility of testing the model without cutting off kurtoses with the focus not on the benchmark replication, but a separate stock universe with specific investment expectations
Threshold for the Size factor	50:50 of NYSE Median breakpoint	40:60 for top 15 stocks	Creating asymmetric portfolios (by the share number) and eliminating unfavorable artificial control of kurtosis and skewness
An indicator of the RMW factor	Operating profitability	ROE	Focus on financial results, which is more often a target for portfolio investors
An indicator of the CMA factor	Change in Total Assets Y-o-Y basis	ROA	Focus on the return on assets
Change in quantiles	Quantiles 30-70 for six portfolios (2x3) composed of about 10,000 shares	For Big-Size quantiles: 33-67-100. Each quantile contains two Top-15 stocks. For Small-Size quantiles: 33-67-100. Each quantile contains three Top-15 stocks	Possibility of more accurately assessing the risk level and return for asymmetric micro-portfolio stocks and evaluating the impact of the largest companies on the cross-section return of individual portfolios
Applying the STARR approach to risks	The portfolio risk comparison was based on Standard Deviation	Stable Tail Adjusted Return Ratio as a Rachev Ratio focuses on the risk-return ratio and takes subadditivity into account through the use of CVaR	Unlike the Sharpe Ratio, STARR allows estimating profitability in a worst-case scenario and uses CVaR

large number of stocks tested. In the process of grouping by the Size factor and quantitative parameters of shares, kurtosis is partially cut off.

In the course of the FF5F model study, attention was paid to the polemical nature of selecting criteria process for the RMW and CMA calculation. Accordingly, it was decided to test this model with some changes in the approaches to selecting financial indicators. Thus, OP/Equity was replaced by ROE and the change in total asset value was replaced by ROA. This allows more closely relating investor targets to traditional financial metrics. This approach was used by Haugen and Baker (1996) and can also be found in Hapsari and Wasistha (2018).

The share allocation within six weighted average portfolios according to three quantiles is carried out by a 33% threshold within each portfolio by BtM, ROE, and ROA parameters. Thus, for BtM, the first 33% threshold quantile is characterized as High, the second 33-66% threshold quantile is Neutral, and the third 67-100% threshold quantile is Low. Accordingly, for ROE, the first quantile is called Robust, the second is Neutral, and the third is Weak. For ROA, the quantiles are Aggressive, Neutral, and Conservative, respectively.

Thus, stocks are allocated across the following portfolios (see Table 2).

3. EMPIRICAL RESULTS

The calculations were run using the Fama and French (2015) methodology and taking the changes made into account (see Table 1). Using the Thomson Reuters Database information, big-size and small-size portfolios of company stocks have been formed (Figures 1 and 2).

Table 2. Small-size and big-size portfolios according to the modified approach

Source: Developed by the authors based on Fama and French (2014).

Small-size			Big-size		
Book to Market (BtM)	Profitability (ROE)	Investment (ROA)	Book to Market (BtM)	Profitability (ROE)	Investment (ROA)
High (SH) Neutral (SN) Low (SL)	Robust (SR) Neutral (SN) Weak (SW)	Conservative (SC) Neutral (SN) Aggressive (SA)	High (BH) Neutral (BN) Low (BL)	Robust (BR) Neutral (BN) Weak (BW)	Conservative (BC) Neutral (BN) Aggressive (BA)

Source: Calculated based on the Thomson Reuters Database (03/21/2019).

BIG-SIZE

BtM				
Name	**Market Cap**	**Book-to-Market Ratio**	**TH**	**Subtype**
JPMORGAN CHASE & CO.	329,216	0.72	17%	High
BERKSHIRE HATHAWAY INC.	493,411	0.69	33%	High
ALPHABET INC.	839,280	0.24	50%	Neutral
APPLE INC.	900,854	0.16	67%	Neutral
MICROSOFT CORPORATION	898,032	0.10	83%	Low
AMAZON.COM, INC.	866,860	0.06	100%	Low

INV (ROA)				
Name	**Market Cap**	**ROV**	**TH**	**Subtype**
FACEBOOK, INC.	469,114	24.3%	17%	Robust
APPLE INC.	900,854	16.1%	33%	Robust
ALPHABET INC.	839,280	14.4%	50%	Neutral
MICROSOFT CORPORATION	898,032	14.1%	67%	Neutral
AMAZON.COM, INC.	866,860	7.8%	83%	Conservative
BERKSHIRE HATHAWAY INC.	493,411	1.1%	100%	Conservative

OP (ROE)				
Name	**Market Cap**	**ROE**	**TH**	**Subtype**
APPLE INC.	900,854	46.1%	17%	Robust
MICROSOFT CORPORATION	898,032	39.3%	33%	Robust
VISA INC.	330,985	36.7%	50%	Neutral
AMAZON.COM, INC.	866,860	28.3%	67%	Neutral
ALPHABET INC.	839,280	18.6%	83%	Weak
BERKSHIRE HATHAWAY INC.	493,411	1.2%	100%	Weak

Figure 1. Share allocation across big-size portfolios

Source: Calculated based on the Thomson Reuters Database (03/21/2019).

SMALL-SIZE

BtM				
Name	**Market cap**	**Book-to-Market Ratio**	**TH**	**Subtype**
BANK OF AMERICA CORPORATION	262,496	1.02	11%	High
SAMSUNG ELECTRONICS CO. LTD	289,349	0.91	22%	High
ROYAL DUTCH SHELL PLC	276,550	0.83	33%	High
EXXON MOBIL	340,817	0.66	44%	Neutral
CORPORATION WALMART INC.	285,529	0.26	56%	Neutral
THE PROCTER & GAMBLE COMPANY	254,311	0.25	67%	Neutral
FACEBOOK INC.	469,114	0.22	78%	Low
JOHNSON & JOHNSON	364,560	0.18	89%	Low
VISA INC.	330,985	0.10	100%	Low

INV (ROA)				
Name	**Market cap**	**ROV**	**TH**	**Subtype**
VISA INC.	330,985	15.8%	11%	Aggressive
SAMSUNG ELECTRONICS CO. LTD	289,349	14.1%	22%	
JOHNSON & JOHNSON	364,560	11.1%	33%	Aggressive
THE PROCTER & GAMBLE COMPANY	254,311	9.1%	44%	Neutral
ROYAL DUTCH SHELL PLC	276,550	6.9%	56%	Neutral
EXXON MOBIL CORPORATION	340,817	6.4%	67%	Neutral
WALMART INC.	285,529	4.3%	78%	Conservative
JPMORGAN CHASE & CO	329,216	1.6%	89%	Conservative
BANK OF AMERICA CORPORATION	262,496	1.6%	100%	Conservative

OP (ROE)				
Name	**Market cap**	**ROE**	**TH**	**Subtype**
FACEBOOK, INC.	469,114	27.9%	11%	Robust
JOHNSON & JOHNSON	364,560	25.5%	22%	Robust
THE PROCTER & GAMBLE COMPANY	254,311	20.3%	33%	Robust
SAMSUNG ELECTRONICS CO. LTD	289,349	19.6%	44%	Neutral
JPMORGAN CHASE & CO.	329,216	14.0%	56%	Neutral
ROYAL DUTCH SHELL PLC	276,550	11.8%	67%	Neutral
BANK OF AMERICA CORPORATION	262,496	11.5%	78%	Weak
EXXON MOBIL CORPORATION	340,817	11.0%	89%	Weak
WALMART INC.	285,529	8.9%	100%	Weak

Figure 2. Share allocation across small-size portfolios

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In the following steps, each portfolio was analyzed using multiple linear regression and ANOVA. The following statements were accepted as the null hypothesis:

- changes in average returns are the same for all portfolios;
- FF5F model does not explain the change in yield in each of the portfolios.

If the null hypothesis is rejected, then the hypothesis that five modified factors are capable of explaining the change in yield in each of the portfolios and that the returns in all the portfolios are different is considered as an alternative one. If the null hypothesis is accepted, it is considered that the testing has proven to be ineffective, and it is not advisable to use the FF5F model to evaluate portfolio return. If the alternative hypothesis is accepted, one has reason to suppose that the modified model is capable of explaining changes in the average portfolio return. Table 3 presents the calculation data.

Table 3. Multiple linear regression results

Source: Calculated based on the Thomson Reuters Database (03/21/2019).

Sort	Variable			
	R-squared	Adj. *R*-squared	*F*-statistics	*P*-value
Big-size BtM	81.7%	80.0%	49.1	0.000
Big-size ROE	83.8%	82.3%	56.9	0.000
Big-size ROA	80.0%	78.2%	44.1	0.000
Small-size BtM	80.6%	78.9%	45.8	0.000
Small-size ROE	78.0%	76.0%	39.1	0.000
Small-size ROA	80.5%	78.8%	45.6	0.000

Multiple linear regression calculations (see Table 3) suggest that all portfolios, except for small-size ROE portfolio, are statistically significant since *R*-squared exceeds 80%. *F*-statistics are also statistically significant for each portfolio since *F*-actual is greater than the *F*-critical value, which is 2.2.

P-value also confirmed statistical significance since it is less than 0.05. Given that the relationship may be non-linear and the number of observations is as low as 60 months, other methods of analysis should be used to interpret the statistical significance of the model and factors.

A separate testing phase is the analysis of the impact of each factor and its statistical significance within each of the portfolios. Table 4 shows the results.

The results show that big-size portfolios have statistically insignificant HML and RMW. In small-size portfolios, in addition to HML and RMW, the CMA ratio is also insignificant.

Small-size ROE is the portfolio with the least statistically significant ratios. Therefore, ROE-based stock grouping for companies with relatively low market capitalization is poor compared to others. Alpha, which indicates excess returns relative to the market, demonstrates the investor's active risk premium. This indicator is statistically significant, which confirms that the construction of such a portfolio is effective.

Table 4. Parameter estimates of the FF5F model

Source: Calculated based on the Thomson Reuters Database (03/21/2019).

Parameter	Rm-Rf	SMB	HML	RMW	CMA	Alpha
Big-size BtM						
Coefficients	0.98	–0.82	0.27	0.14	–1.43	0.90%
T-stat	19.061	–5.139	1.105	0.378	–5.455	2.592
P-value	0	0	0.274	0.707	0	0.012
Big-size ROE						
Coefficients	0.98	–0.95	–0.1	0.24	–1.31	0.85%
T-stat	19.511	–6.289	–0.384	0.607	–4.938	2.581
P-value	0	0	0.702	0.547	0	0.013
Big-size ROA						
Coefficients	0.97	–0.8	0.06	0.45	–1.45	0.80%
T-stat	12.544	–5.04	0.206	1.124	–4.997	2.686
P-value	0	0	0.838	0.266	0	0.01
Small-size BtM						
Coefficients	0.9	–0.28	–0.13	0.09	0.57	0.38%
T-stat	13.614	–2.735	–0.862	0.487	1.967	2.653
P-value	0	0.008	0.393	0.628	0.054	0.01
Small-size ROE						
Coefficients	0.9	–0.2	0.12	0.02	0.49	0.42%
T-stat	10.413	–1.508	0.69	0.106	1.408	2.914
P-value	0	0.137	0.493	0.916	0.165	0.005
Small-size ROA						
Coefficients	0.91	–0.3	0.01	–0.12	0.59	0.45%
T-stat	17.259	–2.511	0.084	–0.569	1.749	3.169
P-value	0	0.015	0.934	0.572	0.086	0.002

It should be borne in mind that the FF5F model should apply the ANOVA to all five factors, not just to changes in the average portfolio yields. The ANOVA results are presented in Appendix A.

- ANOVA results indicate the following:
- Using *F*-test, the null hypothesis was rejected, and the alternative hypothesis was confirmed;

however, the determination coefficient of the entire big-size group is 77%, and this can be a strong relationship between the dependent variable (profitability) and independent variables (the five factors), though they should not be separately excluded from the model. This confirms that portfolios can be balanced in size according to the 40% and 60% thresholds so that they can be averaged, and a statistically significant model can be obtained. Therefore, the authors accept the ANOVA results and argue that the modified FF5F model factors explain the excess average monthly return and changes in the average portfolio return.

- If one considers the impact of the Size factor within each of the three additional factors, it will be found that in portfolios grouped by the BtM factor, the market risk premium (Rm-Rf) decreases with the increase of SMB and CMA. Therefore, these two factors begin to better explain profitability with the decrease in market cap for blue chips.

- HML was supposed to grow as market cap declined since Value Premium stocks had to prevail in the portfolio. However, HML declines with market capitalization. This trend is relevant for all three portfolios, according to BtM, RMW, and CMA factors. The situation is similar for RMW portfolios, except that all factor loadings begin to be more balanced.

CMA portfolios have the most significant reduction in the market risk premium available. All factors show the highest loadings compared to the portfolios from other groups.

Therefore, ROA is better in grouping shares, which demonstrates the impact of all five factors on change in yield.

The calculation of risk indicators allows drawing the following conclusions: all six portfolios, as in FF5M, are left-hand side (LHS); this means that the yield distribution is asymmetric and skewed to the left of the median value. This causes the VaR and C-VaR to be negative. The situation can be explained as follows:

1) the model does not provide for the short position. Therefore, as a result of constant investments, the stock price will increase, so we will profit even in the worst case;

2) LHS portfolio hedging should be performed at a non-standard confidence interval below 95%, as in the 99% case, negative values will only increase. This may also indicate effective share allocation, where a fall in the price of one share will be offset by a rise in the price of another share within the portfolio.

In addition to the first explanation, this can be offset by a monthly portfolio rebalancing, but the FF5F model does not provide this. In the case of constant portfolio rebalancing, an investor is forced to recalculate VaR and C-VaR regularly because without constant portfolio rebalancing the FF5F model calculated "lagged" historical return with outdated prices and outdated risk levels. The authors adhere to the second variant, given that the negative value of VaR and C-VaR results from the simultaneous multidirectional movement of the stock price and is confirmed by high kurtosis. If kurtosis is significantly higher than 3, this means that yields are significantly different from the mean and are not subject to the normal distribution laws. In all portfolios, upside risk should be given particular attention when the investor's expected return is less than the actual return.

Stable Tail Adjusted Return Ratio (STARR) is calculated using the following formula:

$$STARR_{\alpha} = \frac{R_p - R_f}{C\text{-}VaR_{\alpha}\left(R_p - R_f\right)}, \tag{3}$$

where R_p is the portfolio return, R_f is the risk-free rate of return, and $C\text{-}VaR$ is the conditional value-at-risk at α quantile. Table 5 presents the calculation results.

The ambiguous result is that small-size portfolios have lower yields than big-size portfolios; however, extremely high kurtosis rates show that there is a strong tendency to exceed expected returns compared to large portfolios. All STARR ratios are negative due to negative C–VaR values; however, small-size portfolios with smaller negative values show the highest return.

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Table 5. Summary results

Source: Calculated based on the Thomson Reuters Database (03/21/2019).

Portfolio	Monthly return	VaR (95)	Skewness	Kurtosis	C–Var (95)	STARR
Big-size BtM	1.73%	–1.19%	–0.4970	6.4842	–2.23%	–77.50%
Big-size RMW	1.82%	–1.19%	–0.4969	6.4841	–2.23%	–81.60%
Big-size CMA	1.79%	–1.19%	–0.4976	6.4940	–2.24%	–79.82%
Small-size BtM	0.85%	–1.92%	–0.4994	11.5732	–3.00%	–28.46%
Small-size RMW	0.80%	–1.90%	–0.5166	11.8696	–2.98%	–26.78%
Small-size CMA	0.82%	–1.76%	–0.2506	8.3148	–2.72%	–30.06%

CONCLUSION

Thus, by changing parameters for RMW and CMA factors, the threshold proportions for the Size factor, and the quantiles within the portfolios, as well as applying the stratification method to the asymmetric (in terms of amount) investment portfolios, the study has established that the five-factor model can explain the returns of portfolios with negative VaR and C-VaR due to the small number of shares and the type of shares selected (blue chips). According to linear regression in the portfolios, the RMW and CMA ratios were statistically insignificant; however, the monthly Alpha ranged from 0.38% to 0.9%; this indicates the efficiency of such stock allocation across portfolios and higher profitability when compared to the benchmark. ANOVA results confirm the statistical significance of the model. Therefore, we can accept an alternative hypothesis assuming a modified approach to assessing portfolio returns.

It is also concluded that for micro-portfolios of blue chips, the market risk premium is reduced with a simultaneous increase in the Size premium and CMA. This means that these factors better explain changes in yield associated with the decline in market capitalization for blue chips. It is also worthy of note that the HML value should increase with the decline in market cap since Value Premium shares dominated the portfolio; however, HML decreases as market capitalization decreases.

Consequently, six portfolios were received, appropriate calculations were made, and the mean of the excess average monthly yield was attained.

The regression results and ANOVA findings for the FF5F Model are as follows: average monthly excess yield amounts to 11.56%; the statistical significance of the model is 94.4% according to ANOVA.

Thus, high-yield portfolios with near-zero market VaR risk have been obtained. It was also concluded that small-size portfolios, due to high kurtosis, can generate higher returns than big-size portfolios, along with good risk hedging and the lowest STARR ratios.

AUTHOR CONTRIBUTIONS

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APPENDIX A

Table A1. ANOVA results for the BtM group portfolios

Source: Authors' calculations.

Summary output: big-size BtM	
Regression statistics	
Multiple *R*	88.2%
R-squared	77.8%
Adjusted *R*-squared	77.3%
Standard error	0.005
Observations	261

ANOVA	df	SS	MS	F	Significance *F*
Regression	5	0.023	0.005	178.45	0.00%
Residual	255	0.007	0.000		
Total	260	0.029	0.000		

Factors	Coefficients	Standard error	*t*-stat	*p*-value	Lower 95%	Upper 95%
α daily	0.000	0.000	0.538	59.1%	0.000	0.001
R_m-R_fβ	1.116	0.042	26.500	0.0%	1.033	1.199
SMB β	–0.428	0.071	–6.016	0.0%	–0.569	–0.288
HML β	0.761	0.078	9.752	0.0%	0.608	0.915
RMW β	–0.047	0.098	–0.480	63.2%	–0.241	0.146
CMA β	–0.168	0.119	–1.406	16.1%	–0.402	0.067
α annual	0.06%					

Summary output: small-size BtM	
Regression statistics	
Multiple *R*	89.5%
R-squared	80.2%
Adjusted *R*-squared	79.8%
Standard error	0.004
Observations	261

ANOVA	df	SS	MS	F	Significance *F*
Regression	5	0.014	0.003	206.24	0.00%
Residual	255	0.003	0.000		
Total	260	0.018	0.000		

Factors	Coefficients	Standard error	*t*-stat	*p*-value	Lower 95%	Upper 95%
α daily	0.000	0.000	0.048	96.2%	0.000	0.000
R_m-R_fβ	0.907	0.031	29.362	0.0%	0.846	0.968
SMB β	–0.253	0.052	–4.845	0.0%	–0.356	–0.150
HML β	–0.203	0.057	–3.540	0.0%	–0.315	–0.090
RMW β	–0.168	0.072	–2.334	2.0%	–0.310	–0.026
CMA β	0.044	0.087	0.503	61.6%	–0.128	0.216
α annual	0.00%					

Table A2. ANOVA results for the RMW group portfolios

Source: Authors' calculations.

Summary output: big-size RMW (ROE)	
Regression statistics	
Multiple *R*	88.2%
R-squared	77.8%
Adjusted *R*-squared	77.3%
Standard error	0.005
Observations	261

ANOVA	df	SS	MS	F	Significance *F*
Regression	5	0.023	0.005	178.46	0.00%
Residual	255	0.007	0.000		
Total	260	0.029	0.000		

Factors	Coefficients	Standard error	*t*-stat	*p*-value	Lower 95%	Upper 95%
α daily	0.000	0.000	0.538	59.1%	0.000	0.001
R_m-$R_f \beta$	1.116	0.042	26.503	0.0%	1.033	1.199
SMB β	–0.429	0.071	–6.019	0.0%	–0.569	–0.288
HML β	0.760	0.078	9.744	0.0%	0.607	0.914
RMW β	–0.047	0.098	–0.481	63.1%	–0.241	0.146
CMA β	–0.168	0.119	–1.406	16.1%	–0.402	0.067
α annual	0.06%					

Summary output: small-size RMW (ROE)	
Regression statistics	
Multiple *R*	90.3%
R-squared	81.5%
Adjusted *R*-squared	81.1%
Standard error	0.003
Observations	261

ANOVA	df	SS	MS	F	Significance *F*
Regression	5	0.014	0.003	224.73	0.00%
Residual	255	0.003	0.000		
Total	260	0.017	0.000		

Factors	Coefficients	Standard error	*t*-stat	*p*-value	Lower 95%	Upper 95%
α daily	0.000	0.000	–0.239	81.1%	0.000	0.000
R_m-$R_f \beta$	0.918	0.029	31.519	0.0%	0.861	0.976
SMB β	–0.205	0.049	–4.158	0.0%	–0.302	–0.108
HML β	0.035	0.054	0.640	52.3%	–0.072	0.141
RMW β	–0.136	0.068	–2.005	4.6%	–0.270	–0.002
CMA β	0.059	0.082	0.718	47.3%	–0.103	0.222
α annual	–0.02%					

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Table A3. ANOVA results for INV group portfolios

Source: Authors' calculations.

Summary output: big-size INV (ROA)	
Regression statistics	
Multiple *R*	88.2%
R-squared	77.8%
Adjusted *R*-squared	77.4%
Standard error	0.005
Observations	261

ANOVA	df	SS	MS	F	Significance *F*
Regression	5	0.023	0.005	178.584	0.00%
Residual	255	0.006	0.000		
Total	260	0.029	0.000		

Factors	Coefficients	Standard error	*t*-stat	*p*-value	Lower 95%	Upper 95%
α daily	0.000	0.000	0.537	59.2%	0.000	0.001
R_m-R_fβ	1.116	0.042	26.513	0.0%	1.033	1.199
SMB β	–0.428	0.071	–6.017	0.0%	–0.568	–0.288
HML β	0.760	0.078	9.744	0.0%	0.607	0.914
RMW β	–0.048	0.098	–0.485	62.8%	–0.241	0.146
CMA β	–0.168	0.119	–1.410	16.0%	–0.403	0.067
α annual	0.06%					

Summary output: small-size INV (ROA)	
Regression statistics	
Multiple *R*	92.3%
R-squared	85.1%
Adjusted *R*-squared	84.9%
Standard error	0.003
Observations	261

ANOVA	df	SS	MS	F	Significance *F*
Regression	5	0.013	0.003	292.31	0.00%
Residual	255	0.002	0.000		
Total	260	0.015	0.000		

Factors	Coefficients	Standard error	*t*-stat	*p*-value	Lower 95%	Upper 95%
α daily	0.000	0.000	0.569	57.0%	0.000	0.000
R_m-R_fβ	0.895	0.025	36.376	0.0%	0.846	0.943
SMB β	–0.289	0.042	–6.941	0.0%	–0.371	–0.207
HML β	0.120	0.046	2.642	0.9%	0.031	0.210
RMW β	0.014	0.057	0.240	81.0%	–0.099	0.127
CMA β	0.224	0.070	3.215	0.1%	0.087	0.361
α annual	0.04%					