mathematics

Article

An Analysis and Comparison of Multi-Factor Asset Pricing Model Performance during Pandemic Situations in Developed and Emerging Markets

Konstantin B. Kostin [1], Philippe Runge [2] and Michel Charifzadeh [3,*]

[1] Department of Economics and Finance, Saint-Petersburg State University of Economics, 191023 St. Petersburg, Russia; kost_kos@mail.ru
[2] Graduate School, Nordakademie, 22767 Hamburg, Germany; philippe.runge@gmx.de
[3] ESB Business School, Reutlingen University, 72762 Reutlingen, Germany
* Correspondence: michel.charifzadeh@reutlingen-university.de

Abstract: This study empirically analyzes and compares return data from developed and emerging market data based on the Fama French five-factor model and compares it to previous results from the Fama French three-factor model by Kostin, Runge and Adams (2021). It researches whether the addition of the profitability and investment pattern factors show superior results in the assessment of emerging markets during the COVID-19 pandemic compared to developed markets. We use panel data covering eight indices of developed and emerging countries as well as a selection of eight companies from these markets, covering a period from 2000 to 2020. Our findings suggest that emerging markets do not generally outperform developed markets. The results underscore the need to reconsider the assumption that adding more factors to regression models automatically yields results that are more reliable. Our study contributes to the extant literature by broadening this research area. It is the first study to compare the performance of the Fama French three-factor model and the Fama French five-factor model in the cost of equity calculation for developed and emerging countries during the COVID-19 pandemic and other crisis events of the past two decades.

Keywords: Fama French five-factor model; COVID-19; pandemic; crisis; capital asset pricing; cost of equity investment; developed; emerging

Citation: Kostin, K.B.; Runge, P.; Charifzadeh, M. An Analysis and Comparison of Multi-Factor Asset Pricing Model Performance during Pandemic Situations in Developed and Emerging Markets. *Mathematics* **2022**, *10*, 142. https://doi.org/10.3390/math10010142

Academic Editors: Vladimir A. Plotnikov and Christoph Frei

Received: 28 November 2021
Accepted: 24 December 2021
Published: 4 January 2022

1. Introduction

In the past decades, the economic world has been subject to several detrimental crises. The effects of these events were often disastrous and affected the involved markets on economic, political, and sociocultural levels. The occurrence of such crises is a continuous and regular phenomenon on a global scale [1]. A majority of these events affected single countries and their bordering nations only, notably the Russian Financial Crisis from 1998 or the Icelandic Financial Crises between 2008 and 2010. Some of these crises, however, are so devastating in their underlying cause that they harmed whole markets worldwide instead of just a handful of affected countries. Crises of such a magnitude were the burst of the internet bubble 2001, the Global Financial Crisis (GFC, 2007–2008) that led to the Great Recession (2008–2010), or the continuing European debt crisis that began in 2009. These crises are surprisingly comparable in their nature, namely that they spread into affected markets in a relatively slow manner, with effects occurring after several months or even years [2].

In contrast, the most recent crisis showed a completely different picture, with gruesome economic turmoil spreading faster than ever before: The COVID-19 pandemic. This pandemic started as a localized virus outbreak in 2019, which quickly spread to practically every important economic region on the globe. COVID-19 is caused by a virus strain called SARS-CoV-2 and has proven to be a major threat to healthcare and economic systems worldwide. Due to its airborne transmission and the fact that it is able to spread rapidly in a much faster way than other respiratory diseases, healthcare professionals consider it one of the most significant infectious threats at the current moment. Additionally, SARS-CoV-2 is able to damage other organs and trigger massive immune responses in the human body, thereby making it much more difficult to treat infected patients. The range of health-related problems stemming from this virus is extended by the fact that the very cores of economic continuity is targeted by this infection: The interaction between human beings as well as stable population health levels. During the course of the first waves of this pandemic, substantial amounts of the global workforce were forced to work from home, most types of shopping were prohibited, and recreational activities were prohibited for months. These steps—while necessary for the containment of the virus—have shown problematic consequences for markets globally, be it massively increased unemployment numbers from struggling businesses, strong reductions of industry revenues and profit figures, or disruptions of global supply chains. It appeared as if emerging countries were not affected as badly by this crisis on an economic scale, compared to developed countries [2].

Kostin, Runge, and Adams [2] used the Fama French three-factor model to assess the performance of both emerging and developed countries during a pandemic. As the chosen model in this study yielded rather disheartening results, the authors of this study aimed to assess whether the introduction of additional factors may improve the analysis validity regarding the performance of developed and undeveloped countries.

Similar to Blitz and Vidojevic [3], who found that adding additional factors to Fama and French's model did not improve its performance in pricing assets with varying degrees of risk, we wonder whether larger multi-factor models will also show similarly disheartening results [4]. This would further challenge the notion that the simple addition of factors improves the significance of such models. Therefore, this study aims to research the following hypothesis:

- The application of the Fama French five-factor model is unable to provide results, which are superior to the application of the Fama French three-factor model in terms of the performance assessment of developed and emerging countries during pandemic situations.

The remainder of this study is structured as follows. In Section 2 we provide a literature review, outlining the history of capital asset pricing and Fama and French's approach of adding factors to complement the original Capital Asset Pricing Model (CAPM). Section 3 explains the data and methodology of our analysis. The results are presented and discussed in Sections 4 and 5. Section 6 provides a conclusion and outlook on future research.

2. Literature Review

In the history of financial research, a wide variety of factor asset-pricing models have been presented to explain the cross section of stock returns as meaningful and insightful as possible for investors. The earliest model was the renowned CAPM, as introduced independently around the same time by Sharpe [5], Lintner [6], and Mossin [7]. It assumes a rather simple linear relationship between the market risk factor beta and expected return of a specific stock. Due to its simplicity, CAPM has received a remarkable reputation as being one of the most favored asset-pricing models. Black, Jensen, and Scholes [8] confirmed in their study that CAPM is able to produce reliable results after having tested it on NYSE-specific stock data between 1926 and 1966. However, over the years of its existence and application, CAPM has been widely criticized for being based on unrealistic, artificial assumptions, thereby rendering its results meaningless in real-world settings. In this context, Fama and French [9] argue that the model cannot be applied at all as it is impossible to test in its assumed settings. They mention that the model's most significant downfall is its reliance on the market portfolio; an elusive concept, which has theoretically and empirically been challenged as CAPM's basis. In their study, Fama and French [9] argue that the model must employ proxies for the market portfolio, as the market portfolio cannot truly be determined at any given time point. Roll [10] argues in this regard that CAPM is invalid because its implications follow from the market portfolio's efficiency assumption, making it impossible to test these implications in a credible manner. Roll [10] effectively extends on this point by stating that it is impossible to test CAPM realistically unless the full composition of the market portfolio is known. Fama and French [9] added to this criticism that the respective proxies for the true market portfolio used for the application of CAPM can never yield meaningful betas and market premiums, which would be able to explain the variation of any given portfolio. As a consequence, Belen [11] states that it is unlikely for such a proxy to produce betas and market premiums that are able to explain the average return on such portfolios and concludes that such proxies do not work in actual applications, if they already do not work properly in CAPM.

Due to these striking points of criticism, most researchers now consider CAPM invalid and outdated for its assumed field of application. Banz [12] finds that the CAPM neglects a size effect as it appeared to be ineffective for explaining the higher risk adjusted returns of small firms. Consequently, Banz [12] points out the existence of additional factors to be considered in asset pricing. Litzenberger and Ramaswamy [13] discussed a positive relationship between dividend yield and stock returns. Basu [14] finds that price-earnings ratios should be considered in an asset pricing model. Consequently, researchers have suggested to extend CAPM with additional factors in order to allow a more comprehensive and reliable method to explain the variations of underlying assets.

Most prominently, Fama and French [15] published such an extension, calling it the three-factor model as it employed two additional factors on top of beta. Fama and French [15] were able to demonstrate a superiority of smaller companies compared to larger companies, in that they produced higher returns. Additionally, Fama and French [15] were also able to prove that companies holding rather large net assets compared to the company's share market valuation performed much better than companies with smaller net assets compared to their share market valuation. In their field studies, Fama and French [16,17] tested their model on a local and international level and concluded that it is highly effective in calculating return values. The available evidence for the model of Fama and French suggested one fundamental idea at this point, namely that CAPM has significantly been outperformed in its ability to explain the return variations in diversified portfolios. Belyh [18] adds to this point that the three-factor model is able to explain 90% of a portfolio's return variations, while CAPM only achieves a 70% explanation rate. Although this model has received critical acclaim in the financial world, it suffers from several downfalls, which make its currently widespread application at least questionable. The most prominent of these issues is the fact that the three-factor model is fundamentally based on CAPM and only extends its range of factors without actively countering its major issues. As Kostin, Runge, and Adams [2] mention, the three-factor model only expands the initial CAPM formula to address the lack of explanatory power, but it does not address the problematic assumptions as a fundamental basis of CAPM. The authors tested this model to see whether it can provide meaningful data on countries suffering from the current pandemic. They were able to demonstrate an unexpectedly poor performance of the model in this setting. Their findings indicated that other factors must exist, which are more suitable for the explanation of portfolio return variations than the ones used in the three-factor model, as mentioned already.

As this study's hypothesis states, it is likely that the addition of factors does not automatically improve an asset-pricing model's ability to explain the return variations of a given portfolio in every potential setting. The most apparent candidate to test this hypothesis, as mentioned above as well, is the Fama French five-factor model due to it being an advancement of Fama and French's three-factor model. They introduced a new multi-factor asset-pricing model as a direct extension to their three-factor model, extending it by factors for profitability and investment patterns [19]. As stated by Arnold and Lewis [20], Fama and French demonstrated a superiority of share returns from companies with higher profits-to-net-asset rations and that the three-factor model has not included this finding.

Additionally, Fama and French [19] discovered that companies with small changes in their total assets performed much better, compared to companies with larger changes in their total assets. Kostin, Runge, and Adams [2] highlight in this context that the introduction of these factors is particularly noteworthy as they are not risk-related and quality-specific like the rest of the factors in the model. Fama and French [21] even went so far in their direct follow-up study to claim that the five-factor model addresses all the problems of the three-factor model and thus proves to be significantly better than the three-factor set-up. Notwithstanding these statements, the model expresses major flaws, which raised certain objections to its widespread use. As Kostin, Runge, and Adams [2] mentioned, the density of literature containing actual criticism of this model is rather small. While a wide variety of studies have been published, which aim to prove the model in specific settings globally, only a miniscule number of articles have been published which directly raise criticism and suggest improvements to the model.

Blitz et al. [4] have presented the most prominent article in 2018. Most notably, Blitz et al. [4] highlight five significant concerns with the development and application of this model; four of them being relevant for the setup of this study. In an earlier study, Blitz and Vidojevic [3] had already found that the exposure to beta in the cross-section of stocks is not directly compensated by higher returns, "regardless of whether one controls for the additional factors proposed by Fama and French (2015)" (p. 34) [3]. Blitz et al. [4] state that the five-factor model is fundamentally flawed by still being based on CAPM. While additional factors have been introduced to increase the model's ability to explain asset returns, the actual issue of CAPM's unrealistic and insupportable assumptions still prevail in the five-factor model, thereby raising skepticism on whether this model can yield any meaningful results. Secondly, Blitz et al. [4] note that the model is still unable to explain the momentum premium. This is particularly surprising, as the momentum anomaly was already well researched by the time the five-factor model had been published. Fama and French [22] themselves even stated that momentum has become an increasingly important factor in financial research, acknowledging that it cannot be explained by both CAPM and their own three-factor model. Blitz et al. [4] add as well that the added factors may not be as robust as required to justify their addition to the model. Fama and French [22] even state in their own work that the investment factor—also being defined as asset growth—is considered not resilient by the authors, thereby raising concern about the applicability of these factors.

Lastly, Blitz et al. [4] challenge the economic rationale of the model, as there appears to be an ambiguous approach to the addition of the factors. Precisely, the previously introduced factors in the three-factor model were all risk-related. The added factors in the five-factor model, however, cannot be considered risk-related any longer. As Blitz et al. [4] conclude, risk-based investors would expect low-profitability companies with higher risk profiles to outperform high-profitability companies with reduced risk profiles in a classical approach, instead of the other way around as listed in the five-factor model. They challenge this ambiguity as such an omission would lead the model away from a risk-based approach, thereby opening room for the addition of practically any factor until the model eventually fits the purpose [4].

Blitz et al. [4] also mention it as an issue that the five-factor model does not end the search for comprehensive asset-pricing models. However, it has never been stated in the available literature that Fama and French sought to provide a perfect, comprehensive model for all economic situations. This point will therefore not be taken into further consideration.

In addition, further doubt is raised to the validity of the five-factor model by Racicot and Rentz [23] who state that the model only performs well if a standard econometric estimator is used, like Ordinary Least Squares (OLS) estimations. In order to challenge these positive results, Racicot [24] developed a method for the analysis of such a model using a Generalized Method of Moments (GMM) approach. By applying their approach, Racicot [24] identified that explanatory power of the Fama French five-factor model sunk significantly compared to only following the OLS approach.

It is also surprising to see that the five-factor model omits other potential risk factors for asset pricing, which were already known and being researched at the time of the introduction of the model. Racicot et al. [25] augmented the model by an illiquidity factor to test whether this proxy may also be relevant in terms of asset pricing and used the method from Racicot [24] to test for the relevance of this factor. Racicot et al. [25] argue in this regard that illiquidity may have a significant effect on asset pricing. These results are partially supported by de Carvalho et al. [26] who tested the augmented Fama French five-factor model in the Latin American emerging stock markets using an OLS approach first, followed by GMM. Looking at OLS alone, de Carvalho et al. [26] identified that the augmentation of the model allows a better explanation of returns in the researched markets. However, when applying the GMM approach, Carvalho et al. [26] found that results between the five-factor model and the augmented version did not differ significantly.

Taking all these points together, one can see that the applicability of the five-factor model appears to be limited and continues to be challenged on a wide basis. One must question the notion at this point that the five-factor model constitutes a robust and fully reliable improvement to the currently available multi-factor asset-pricing models. This study aims at providing empirical evidence of the validity of the Fama French five-factor model, challenging its applicability in a crisis setting such as the current COVID-19 pandemic.

3. Methodology

3.1. Model

This study employs the Fama French five-factor model to calculate the cost of equity from the market data of the chosen sample. The used regression equation is as follows:

$$R_{i,t} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \varepsilon_{i,t} \quad (1)$$

while $R_{i,t}$ is the return of portfolio i for month t, SMB_t (Small Minus Big) is the variable capturing the size, i.e., the difference between returns of diversified portfolios of small and big stocks, HML_t (High Minus Low) is the difference between the return of diversified portfolios of high and low B/M stocks, RMW_t (Robust Minus Weak) is the difference between companies with robust and weak operating profitability, CMA_t (Conservative Minus Aggressive) is the difference between the return of companies investing conservatively and companies investing aggressively, and $e_{i,t}$ denotes the error term of portfolio i for month t.

Comparable to Miss, Charifzadeh, and Herberger [27] we analyze different time periods around crisis events that potentially have the power to induce substantial frictions in capital markets. Kostin, Runge, and Adams [2] divided the cost of equity calculations into several subsections as benchmarks and to facilitate the analysis of relevant periods. This study will employ the same subsections to allow a comparison of the results of the calculations based on both the Fama French three-factor and Fama French five-factor model. The subsections are:

- Full Data Period;
- The period during the COVID-19 Pandemic Months;
- The period between the Global Financial Crisis (GFC) and COVID-19;
- The period during the Global Financial Crisis (GFC);
- The period before the Global Financial Crisis (GFC).

3.2. Test of Model Performance

Following the suggestion of Gibbons, Ross, and Shanken [28], this study will apply the GRS F-test statistic to evaluate the Fama French five-factor model's performance on the chosen datasets by testing the null H_0: $\alpha_i = 0$ jointly for all i. It is conducted by performing an OLS regression first. Afterwards, the intercept of the alpha values is calculated. Lastly, it tests whether the joint value of the alphas is zero. The equation for the test statistic is constructed using the intercepts and error terms as outlined in Equation (1). Let $\alpha_i = (\alpha_{1,\ldots,\alpha_n})$ and let $\varepsilon_i = (\varepsilon_{1,\ldots,}\varepsilon_n)$ be n-vectors, which include the intercept values and error terms from Equation (1). Under the assumption that the error term (ε_i) is normally and evenly distributed with zero means and non-singular covariance matrix $\sum$, the F-test statistic is given by:

$$F = \left(\frac{T}{N}\right)\left(\frac{T-N-L}{T-L-1}\right)\left[\frac{\hat{\alpha}'\hat{\sum}^{-1}\hat{\alpha}}{1+\overline{\mu}_L{}'\hat{\Omega}^{-1}\overline{\mu_L}}\right] \tag{2}$$

where$T$ represents the size of the sample, N is the number of portfolios, L is the number of explaining factors, $\hat{\alpha}$ being a $N \times 1$ vector of the estimators for the vector of intercepts $\alpha \equiv \alpha_1, \ldots, \alpha_n)$, $\hat{\sum}$ being an unbiased estimate of the residual covariance matrix in the sample set, $\overline{\mu}_L$ being an $L \times 1$ vector of the factor portfolios' sample means, and $\hat{\Omega}$ being an unbiased estimate of the factor portfolio's covariance matrix.

The current literature suggests that additional tests should be conducted to address concerns about non-normal and serially-autocorrelated errors. As Racicot et al. [25] suggest, weakness in these areas can present a significant problem as choosing instruments being weak in terms of error robustness may transform the chosen estimator into a biased version of itself. Cakici, Fabozzi, and Tan [29] suggested a test for these error terms based on a Generalized Method of Moments (GMM) approach in connection with the GRS test. However, their proposed method is not strictly suitable to panel-based data as used in this study. Racicot et al. [25] introduced a more fitting estimator in their study, which would be able to tackle these error-specific issues as it is specifically designed to address panel data regressions. Racicot et al. [25] based their approach on higher moments and cumulants and were able to demonstrate that their suggested estimator can be used together with the GMM method to construct a more reliable estimation approach than the current GMM approach. As mentioned above, Racicot et al. [25] applied their approach on an augmented version of the Fama French five-factor model. It is likely that their approach would therefore also work on applications of the original five-factor version without augmentations.

However, the authors chose not to apply this approach as the GRS test appears to sufficiently account for non-normal error terms already. Affleck-Graves and McDonald [30] described that the GRS is not generally sensitive to non-normal sample distributions if they are within typical levels of nonnormality. Affleck-Graves and McDonald [30] rightfully add that the power of the GRS test can be misstated significantly, but only in such settings where the levels of nonnormality are severe. This often occurs in such settings where sample sizes are considerably large and span several decades of data. In such settings, it cannot be ruled out that periodic effects are present, which explain non-trivial deviations from a normal distribution. As the chosen dataset does not extend beyond 20 years, the authors believe that there is no reason to assume a non-trivial deviation from normality, which would require further validation of the data.

Following H_0 that all regression intercepts equal zero, the GRS statistic expresses an F distribution with N and T-N-L degrees of freedom.

The expectation is that the application of this test will provide meaningful insights into the capability of the asset-pricing model to help explain the variations in returns for a particular portfolio. A higher value implies that the value of the combined intercepts deviates substantially from zero, meaning that the model's factors are insufficient to effectively explain the variation of the portfolio's return. Accordingly, a higher value of the GRS statistic equals a higher joint alpha value that strays further from zero. Such a result constitutes an insufficient performance of the tested asset-pricing model.

3.3. Data

As mentioned above, this study aims to compare previous findings from an earlier study of Kostin, Runge, and Adams [2] applying the Fama French three-factor model in emerging and developed markets with the application of the Fama French five-factor model in the same markets during the COVID-19 pandemic timeframe. Consequently, the same data sets will be used to test the model. We employ monthly stock data from four leading indices of both developed markets (Nasdaq Composite—US, FTSE100—United Kingdom, Nikkei 225—Japan, DAX30—Germany) and four economically strong emerging markets (MOEX—Russia, Shanghai Composite—China, IBOVESPA—Brazil, Mexico IPC—Mexico) for the calculation of the cost of equity.

For the developed countries, the decision to include the US, Japan, and the United Kingdom as representatives of this category was made based on their GDP, where these countries rank highest in comparison to all other developed countries. The same criterion was applied to the emerging countries as well. It must be noted in this regard that India would have ranked considerably higher than the countries chosen for this study in normal, less problematic economic settings outside of a pandemic situation. However, this comparison would only be possible for a timeframe that does not express such significantly negative effects on whole markets like the COVID-19 pandemic. In terms of India, the authors considered a substantial risk of market and healthcare infrastructure collapse. This was backed up by India being ranked considerably lower in terms of healthcare levels by the Legatum Prosperity Index. India listed on rank 101, while China, Russia, Brazil, and Mexico were listed on ranks 54, 76, 70, and 68. The authors suspected that India may be unable to buffer the effects of this pandemic with uncertain effects on the country's economy as a whole and may therefore be unsuitable for inclusion in this study. Due to the severe effects of COVID-19 on healthcare systems, the authors anticipated that the framework of countries like the chosen examples showed stronger resilience against pandemic situations and would therefore produce more trustworthy and reliable data.

The stock data has been taken from Yahoo Finance. To allow sufficient robustness and comparability, the datasets have been limited to range from January 2000 to the end of August 2020. Country-level data for Russia were not available before October 2000. In addition, we used return data from sample firms for two developed markets and two emerging markets to compute the return for investors seeking an investment in companies of these regions. The firms used in our study are Apple and Walmart for the US, Daimler and SAP for the German market, Lukoil and Gazprom for Russia, and SAIC Motor as well as China Mobile for the Chinese market.

While some previous studies distinguish between the Subprime Crisis from 2007 to 2008 and the Global Recession from 2008 to 2010, we refer to this entire period from 2007 to 2010 as GFC. Monetary data sets used in our study were converted to U.S. dollars; excess returns were computed relative to the one-month U.S. Treasury bill rate. Data before January 2000 and after August 2020 has been excluded. This is consistent with French's (2017) conclusion that most investors look at only four years of data rather than several decades. Such larger datasets may typically be used to investigate the general validity of asset pricing models. However, they do not necessarily serve as useful decision-making tools for investors in a real-world setting. Kostin, Runge, and Adams [2] mention that this particular time window between 2000 and 2020 spans significant financial crises like the GFC and the Global Recession, allowing a concise assessment of return data before, during, and after these events. Additionally, this timeframe allows the inclusion of substantial amounts of data from the COVID-19 pandemic and a comparison of the pandemic-related data to previous financial crises. No data after August 2020 has been included in this study to avoid a dilution of the reliability of this study's results and the study from Kostin, Runge, and Adams from 2021.

We would like to note that the COVID-19 pandemic was still persisting while this study was being written, with already worsening case numbers. New governmental restrictions and negative economic effects cannot be excluded at this stage and may exert substantial influence on the below-presented results. Therefore, additional data will be available for future analysis of such effects on these markets, e.g., supply chain interruptions or additional trade restrictions.

3.4. Implementation of Asset Pricing Factors

In our study, we consider five-factors that are used as explanatory values in the regression Equation (1). These coefficients are the market factor, SMB factor, HML factor, RMW factor, and investment pattern (CMA) factor. We retrieved the factor data for both developed and emerging markets from French's data library, accessible at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html, (accessed on 27 November 2021). The factors of the developed markets include data from 23 developed countries. The factors of the emerging markets incorporate information from 26 emerging countries. Further detailed information as to how these factors for both developed and emerging markets have been obtained can be found in French's data library at the following websites: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_5developed.html, (accessed on 27 November 2021), https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_5emerging.html, (accessed on 27 November 2021).

4. Results

This section presents the empirical results of this study and compares it with the results of Kostin, Runge, and Adams [2].

4.1. Analysis Results for Stock Market Index Data—Developed and Emerging

A mutual agreement exists in the literature that asset-pricing models are valid if their intercept value is as close to zero as possible. Fama and French [9] even go so far to state that asset-pricing models only support their results if there is no possibility to group assets into portfolios so that their intercept values are different from zero. As illustrated in Table 1, the Fama French five-factor model succeeds in producing such alpha values, which are considerably close to zero for the chosen market indices in both the developed and undeveloped markets. This is also underlined by the MAVA (mean average value of alphas) value for both developed and undeveloped countries, which is practically zero as well.

Table 1. Fama French five-factor regressions for country indices—developed and emerging; *: $p < 0.05$.

Country Data	α	t(α)	β	SMB	HML	RMW	CMA	R^2 (Adjusted)
US	0.01 *	4.53	0.96 *	0.12	−0.76 *	−0.99 *	−0.15	0.86
UK	−0.003 *	−2.48	0.74 *	−0.21 *	0.07	0.00	0.03	0.70
Japan	−0.002	−0.94	0.81 *	0.44 *	0.26	0.03	−0.36	0.53
Germany	0.001	0.62	1.01	-0.24	−0.14	−0.50 *	0.06	0.65
Russia	0.01 *	2.00	−0.02	1.25 *	0.93 *	−0.02	−1.24 *	0.10
China	−0.001	−0.15	0.56 *	0.38	0.27	0.18	0.10	0.18
Brazil	0.001	0.61	0.89 *	−0.71 *	0.24	−0.27	0.27	0.65
Mexico	0.003	1.27	0.67	−0.09	−0.16	0.15	0.21	0.53
GRS Developed: 9.18 *				MAVA DEV: 0.003			Average R^2 DEV: 0.68	
GRS *p*-value: 2.766×10^{-7}								
GRS Emerging: 7.07 *				MAVA EM: 0.003			Average R^2 EM: 0.36	
GRS *p*-value: 1.288×10^{-5}								

Three out of the eight alphas showed negative values, while five alpha values came back positive. This is identical to the regression of the Fama French three-factor model as shown in Table 2.

However, three of the alpha values were statistically significant at the 0.05 level for the Fama French five-factor model regression, while only one value was statistically relevant in the Fama French three-factor model regression. In contrast, all β values proved statistically significant at the 0.05 level for the three-factor level, while only five β for the five-factor value were statistically significant. Five out of eight SMB values were statistically significant for the Fama French three-factor model and four out of eight SMB values were statistically significant for the Fama French five-factor model. For both models, two out of eight HML values came back as statistically significant. Two out of eight RMW values were statistically significant and only one CMA value was statistically significant. As shown in Table 2, the Fama French three-factor model produced an acceptable R^2 average of 0.67 for the developed countries and a rather disappointing R^2 average for the emerging countries. Unexpectedly, the Fama French five-factor model did not improve this value significantly with an average R^2 of 0.68 for the developed countries and 0.36 for the emerging countries. This indicates that other factors must exist which allow the explanation in the variation of the dependent variable, but have not been captured in both the three-factor and Fama French five-factor model. As with the three-factor model, it should be noted that the R^2 average for the emerging countries in the Fama French five-factor model is heavily influenced by the remarkably low R^2 values of Russia and China, while Mexico and Brazil produce reasonably acceptable R^2 values. Table 2 also outlines the GRS test results for the Fama French three-factor model with a value of 14.29 for the developed countries and 7.55 for the emerging countries. In contrast, the GRS test value for the Fama French five-factor model improved to 9.18 for the developed countries and 7.07 for the emerging countries. Consequently, the use of the Fama French five-factor model is strongly rejected at this point as well. The p-values for both GRS test series are practically zero below the 0.05 significance level. This indicates that H_0: $\alpha = 0$ for the Fama French five-factor model has to be rejected.

Table 2. Fama French three-factor regressions for country indices—developed and emerging; * $p < 0.05$.

Country Data	α	t(α)	β	SMB	HML	R^2 (Adjusted)
US	0.003	1.71	1.10 *	0.36 *	−0.88 *	0.82
UK	−0.003 *	−2.70	0.74 *	−0.21 *	0.09	0.70
Japan	−0.003	−1.26	0.85 *	0.46 *	0.08	0.53
Germany	−0.0005	−0.25	1.06 *	−0.13	−0.13	0.64
Russia	0.01	1.95	0.19 *	1.32 *	0.39	0.08
China	0.0002	0.06	0.53 *	0.34	0.25	0.18
Brazil	0.0007	0.27	0.86 *	−0.70	0.42 *	0.65
Mexico	0.004	1.73	0.62 *	−0.15 *	−0.13	0.53
GRS Developed: 14.29 *	MAVA DEV: 0.002				Average R^2 DEV: 0.67	
GRS *p*-value: 2.367×10^{-11}						
GRS Emerging: 7.55 *	MAVA EM: 0.003				Average R^2 EM: 0.36	
GRS *p*-value: 5.388×10^{-6}						

From an investor's viewpoint, the cost of equity displays the necessary return of investments in equity, e.g., buying stocks. Consequently, Kostin, Runge, and Adams [2] figured that a comparison could be made between the cost of equity of such investments in specific areas during defined timeframes. Investors would be able to see in that case what return values they could expect in these markets and what levels of risk they would need to accept to reach these expected values. Table 3 outlines the cost of equity calculations for the Fama French three-factor model [2]. Table 4 outlines the cost of equity calculations for the Fama French five-factor model. The tables include average values for the predefined periods for a facilitated overview of the results.

On average, the developed countries showed a cost of equity of −0.63% before the GFC, using the Fama French five-factor model. During the GFC, the developed countries exhibited an average cost of equity of 0.52%, skewed, however, by a strongly negative value of the US. The average cost of equity for the emerging countries during the GFC was 7.54% and 5.31% during the GFC. The average cost of equity after the GFC rose to 5.27% for the developed countries and dropped to 3.59% for the average countries. This result is not surprising and in line with Griffin, Kelly, and Nardari [31] who outlined that emerging markets may show superior recovery potential following the occurrence of economic crises in comparison to developed countries. The average cost of capital during the COVID-19 pandemic ranged at 15.05% for the developed countries using the Fama French five-factor model; approximately three times higher than the value of the Fama French three-factor model for the same period. However, the Fama French five-factor model also revealed an average cost of equity capital of 130.61% for emerging countries in contrast to roughly 88% from the Fama French three-factor model. It is important to keep in mind at this point that these periods constitute small subsets of the full data set and therefore only allow a narrow data analysis. Consequently, the cost of equity for the full data set has been calculated as well to factor in the effects of the GFC as well as of the COVID-19 pandemic for a more realistic estimate. By following this approach, it is also possible to alleviate the distorting effects of the negative cost of equity values. These resulted from significantly large arrays of negative return data during the GFC and COVID-19 pandemic period and should be viewed with caution. These values indicate severely negative economic effects on the observed markets, which drew a majority of these values into a negative range. The average cost of equity for developed countries ranged at 2.36% with the Fama French five-factor model, while the three-factor model showed an average cost of equity of 5.52%. In contrast, the average cost of equity for emerging countries increased slightly to 7.62% with the Fama French five-factor model, compared to 7.49% for the three-factor model. The use of the Fama French five-factor model revealed that the developed markets performed better overall than the emerging markets, as the emerging markets' average cost of equity was about two times higher than the average cost of equity for emerging countries in the Fama French five-factor model. These results contrast the findings of Griffin, Kelly, and Nardari [31], meaning that the economic performance of the emerging countries becomes worse compared to the developing countries once the COVID-19 pandemic data is included in the calculation. It is noteworthy at this point that the COVID-19 pandemic is still ongoing and continues to have negative short- to mid-term economic effects. Therefore, it is not possible to fully evaluate the further impact of the pandemic fully on the cost of equity for these markets.

Table 3. Fama French three-factor model—results of cost of equity calculations for developed and emerging countries; negative values in italics.

Country Data	Full Period	COVID-19 Period	Between GFC and COVID-19 Period	During GFC	Up to GFC
US	3.77%	18.91%	12.08%	*−4.39%*	*−14.64%*
UK	5.36%	*−1.80%*	8.07%	*−3.24%*	3.11%
Japan	6.49%	22.13%	7.23%	*−3.38%*	8.71%
Germany	6.45%	*−17.05%*	11.72%	*−4.77%*	1.84%
Russia	5.60%	146.44%	0.30%	5.16%	6.97%
China	7.41%	*−15.39%*	4.52%	9.08%	6.72%
Brazil	11.38%	185.19%	7.77%	7.75%	14.15%
Mexico	5.55%	35.71%	3.18%	9.92%	4.86%
Average Developed	5.52%	5.55%	9.78%	*−3.95%*	*−0.25%*
Average Emerging	7.49%	87.99%	3.94%	7.98%	8.18%

4.2. Analysis Results for Company Stock Data—Developed and Emerging

As presented in Table 5, the Fama French five-factor model also succeeds in generating alpha values, which are close to zero for all chosen company-level stock data sets in the developed and emerging markets. This is also supported by near-zero MAVA values for both data sets. The regression results for the Fama French three-factor model can be found below for a comparison of the results (Table 6).

Table 4. Fama French five-factor model—results of cost of equity calculations for developed and emerging countries; negative values in italics.

Country Data	Full Period	COVID-19 Period	Between GFC and COVID-19 Period	During GFC	Up to GFC
US	*−0.50%*	15.63%	12.20%	*−5.33%*	*−17.37%*
UK	5.29%	21.39%	8.71%	2.96%	6.79%
Japan	5.76%	43.72%	0.50%	0.55%	9.36%
Germany	*−1.11%*	*−11.56%*	*−0.34%*	3.90%	*−1.30%*
Russia	4.83%	238.79%	0.03%	*−7.27%*	5.17%
China	8.45%	10.00%	5.22%	17.62%	6.80%
Brazil	10.47%	215.42%	4.76%	6.55%	9.58%
Mexico	6.73%	58.22%	4.35%	4.34%	8.61%
Average Developed	2.36%	15.05%	5.27%	0.52%	*−0.63%*
Average Emerging	7.62%	130.61%	3.59%	5.31%	7.54%

Table 5. Fama French five-factor regressions for company stock data—developed and emerging; * $p < 0.05$.

Company Data	α	t(α)	β	SMB	HML	RMW	CMA	R^2 (Adjusted)
Apple	0.025 *	4.00	1.04 *	0.16	-0.22	0.38	−1.78 *	0.35
Walmart	0.0005	0.17	0.50 *	−1.00 *	−0.58 *	0.43	0.80 *	0.23
Daimler AG	−0.002	−0.41	1.37 *	0.29	0.62 *	0.28	−0.82 *	0.46
SAP	0.014 *	2.70	0.97 *	−0.76 *	−0.93 *	−1.87 *	0.11	0.39
Lukoil	0.007	1.24	0.92 *	−0.49	0.55	−0.39	−0.61	0.39
Gazprom	0.009	1.06	0.74 *	1.08 *	0.38	−1.28	−0.11	0.17
SAIC Motor	0.006	0.76	0.62 *	0.20	0.74	0.31	0.10	0.10
China Mobile	0.0001	0.03	0.93 *	−0.94 *	−1.14 *	0.90 *	1.38 *	0.42
GRS Developed: 18.64 *		MAVA DEV: 0.0069			Average R^2 DEV: 0.36			
GRS p-value: 8.66×10^{-15}								
GRS Emerging: 3.56 *		MAVA EM: 0.0028			Average R^2 EM: 0.27			
GRS p-value: 6.805×10^{-5}								

Table 6. Fama French three-factor regressions for company stock data—developed and emerging; * $p < 0.05$.

Company Data	α	t(α)	β	SMB	HML	R^2 (Adjusted)
Apple	0.02 *	3.88	1.25 *	0.19	−1.11 *	0.33
Walmart	0.004	1.38	0.34 *	−1.15 *	−0.16	0.20
Daimler AG	−0.0023	−0.50	1.46 *	0.28	0.20	0.46
SAP	0.006	1.27	1.17 *	−0.34	−0.96 *	0.34
Lukoil	0.005	0.90	1.04 *	−0.37	0.46	0.39
Gazprom	0.003	0.36	0.84 *	1.31 *	0.73	0.17
SAIC Motor	0.008	1.04	0.58 *	0.14	0.68 *	0.11
China Mobile	0.006	1.36	0.67 *	−1.20 *	−0.96 *	0.37
GRS Developed: 20.47		MAVA DEV: 0.008		Average R^2 DEV: 0.33		
GRS p-value: 3.331×10^{-16}						
GRS Emerging: 4.17		MAVA EM: 0.0015		Average R^2 EM: 0.26		
GRS p-value: 0.002						

For the Fama French five-factor model, two alpha values were statistically significant, while only one of the alphas for the Fama French three-factor model was significant. Both models produced statistically significant values of β for all eight companies. Four SMB values were statistically significant for the Fama French five-factor model with three SMB values being statistically significant for the Fama French three-factor model. Four HML values came back statistically significant for both the five- and the three-factor model. Two RMW values were statistically significant. Three CMA values were statistically significant. Additionally, the Fama French five-factor model presented dissatisfying R^2 values similar to those of the Fama French three-factor model; similarly for the exemplary developed and emerging market companies. The developed company set showed an average R^2 of 0.36, while the emerging company set showed an average R^2 of 0.27. As for the country-level data of the emerging country indices, this indicates that other factors must exist in these markets—on a company level this time—which explain the variation in the dependent variable, but are not included in the current model. Additionally, the use of the Fama French five-factor model is also rejected on a company data level, indicated by GRS test results of 18.64 for developed companies and 3.56 for emerging companies. Although both values improved by using the Fama French five-factor model, the results are still insufficient. Both values are statistically significant, which shows that H_0: $\alpha = 0$ for all of i of the used Fama French five-factor model can be rejected for both the companies in developed as well as in emerging markets.

As with the country-level data, the cost of equity was calculated as well for the sample companies in both developed and emerging markets. The results can be found in Tables 7 and 8.

Table 7. Fama French five-factor model—results of cost of equity calculations for developed and emerging companies; negative values in italics.

Company Data	Full Period	COVID-19 Period	Between GFC and COVID-19 Period	During GFC	Up to GFC
Apple	2.61%	*−59.15%*	19.26%	3.28%	*−7.10%*
Walmart	6.38%	7.39%	11.45%	1.69%	2.35%
Daimler AG	2.41%	*−180.16%*	*−0.19%*	15.57%	5.69%
SAP	*−9.92%*	*−77.31%*	*−4.78%*	*−8.30%*	*−22.54%*
Lukoil	10.00%	174.53%	*−0.98%*	11.32%	26.78%
Gazprom	6.06%	350.41%	*−9.33%*	16.33%	10.35%
SAIC Motor	12.59%	25.56%	5.41%	28.06%	10.86%
China Mobile	6.79%	*−185.30%*	14.39%	2.44%	*−13.30%*
Average Developed	0.37%	*−77.31%*	6.44%	3.06%	*−5.40%*
Average Emerging	8.86%	91.30%	2.37%	14.54%	8.67%

Table 8. Fama French three-factor model—results of cost of equity calculation for developed and emerging companies; negative values in italics.

Company Data	Full Period	COVID-19 Period	Between GFC and COVID-19 Period	During GFC	Up to GFC
Apple	5.02%	51.09%	14.77%	*−7.68%*	*−5.95%*
Walmart	1.84%	91.35%	6.46%	*−0.91%*	1.58%
Daimler AG	9.75%	*−47.26%*	15.50%	*−6.56%*	8.46%
SAP	4.56%	*−21.86%*	12.15%	*−2.14%*	*−15.44%*
Lukoil	12.96%	274.48%	7.30%	6.54%	21.87%
Gazprom	12.79%	284.06%	3.55%	12.11%	16.56%
SAIC Motor	10.84%	*−59.76%*	4.45%	22.73%	16.92%
China Mobile	0.40%	*−200.33%*	4.05%	*−13.82%*	*−15.03%*
Average Developed	5.29%	18.33%	12.22%	*−4.32%*	*−2.84%*
Average Emerging	9.25%	74.61%	4.84%	6.89%	10.08%

The same sub-periods have been assessed for the analysis of the exemplary companies. It comes as no surprise that the result patterns are quite similar to the country index movements. However, the magnitude of the company-specific results differs from the results of the country indices. For the period before the GFC, the average cost of equity capital for firms in developed markets was −5.4%, while firms in emerging markets had an average cost of equity of 8.67% in the Fama French five-factor model. In contrast, the Fama French three-factor model showed an average cost of equity capital of −2.84% for the developed market companies and 10.08% for the emerging market companies.

The average cost of equity capital for the time during the GFC was 3.06% for the developed market companies and 14.54% for the emerging market companies in the Fama French five-factor model. The Fama French three-factor model showed a negative average cost of equity capital for developed market companies of −4.32% and an average cost of equity of 6.89% for the emerging market companies.

As with the market data, the company-specific results showed the same pattern for the period between the GFC and COVID-19 pandemic. For the Fama French five-factor model, the average cost of equity for the developed market companies was 6.44% and 2.37% for the emerging market companies. The Fama French three-factor model showed a larger difference with an average cost of equity capital of 12.22% for the developed market companies and 4.84% for the emerging market companies.

During the chosen COVID-19 period, the average cost of equity for firms in developed markets was −77.31% and 91.3% for emerging market companies with the Fama French five-factor model. In comparison, the Fama French three-factor model showed an average cost of equity of 18.33% for the firms in developed markets and 74.61% for the emerging market firms.

Similar to the market index data, the average cost of equity for the full period has been calculated as well for results that are more robust. In this context, the Fama French five-factor model showed an average cost of equity of 0.37% for the developed market companies and 8.86% for the emerging market companies. It must be noted that the value for the developed market companies is heavily skewed by the negative cost of equity of SAP in the Fama French five-factor model, which potentially distorts the actual average cost of equity. Further research may be needed to determine why SAP showed such a problematic value. The Fama French three-factor model, in contrast, showed an average cost of equity for the developed market companies of 5.29% and 9.25% for the emerging market companies. With the given data, one may conclude from the use of the Fama French five-factor model that the emerging market companies performed worse than the developed market companies did as their average cost of equity was 22 times higher than the average cost of equity of the developed market companies.

5. Discussion

The above-attached Tables 1 and 5 show that the underlying Fama French five-factor model only partially performed as expected and did not yield significantly better results than the Fama French three-factor model as used by Kostin, Runge, and Adams [2] in the same setting. As with the Fama French three-factor model, it is surprising to see—as an initial measurement of model performance—that the R^2 value of the used index and company-specific data differed significantly within the datasets, with values diverging between 0.1 to >0.8 for the country index data and 0.1 to >0.4 for the company-specific data. While no specific consensus exists for the classification of goodness of fit of a model in terms of R^2, Zikmund et al. [32] specified a rough-and-ready rule for a classification of this value:

- $R < 0.3$ no or very weak size effect;
- $0.3 < r < 0.5$ weak size effect;
- $0.5 < r < 0.7$ moderate size effect;
- $r > 0.7$ strong size effect.

It is intriguing to see that the regression results of the developed markets from the Fama French five-factor model only showed a strong size effect for two countries, the US and the UK. A merely moderate size effect appeared for Japan and Germany. These findings are in line with Kostin. Runge, and Adams [2] who received similar results for these indices using the Fama French three-factor model. However, these results are considerably satisfying as the underlying Fama French five-factor model is able to explain 52 to 82% of the variance of the dependent variable, allowing a reasonably reliable calculation of the cost of equity. Unfortunately, these findings are almost directly rejected to some extent by the presented GRS statistic results as shown in Tables 1 and 5. These values strongly deviate from zero for the underlying country index data. This suggests that the underlying model is insufficient in explaining the variations in return results of the researched country-specific market data. Similar to the data from the Fama French three-factor model, the emerging market indices showed weak to moderate size effects for the independent variable of the Fama French five-factor model. R^2 values ranged between 0.1 and <0.7. Similar to the developed country indices, the GRS test statistic suggests a rejection of the use of this model as well. While the test result of 7.07 is better than the developed market GRS test result of 9.18 for the Fama French five-factor model, it still strays considerably far from zero. A similar situation exists for the company-specific data. It is rather disheartening to see that both the developed and emerging companies do not reach an R^2 of >0.5. For this particular case, the independent variables from the Fama French five-factor model are only able to explain between approximately 10% and 46% of the variation in the dependent variable. In addition, the results from the application of the GRS test statistic further underline the dissatisfying performance of the model in this setting. The GRS test statistic is twice as large for the developed company data as the developed market index data, indicating a strong lack of suitability of this model here. A certain improvement occurred in the emerging market company data sets where the GRS test value was half as large as the value for the emerging market indices. However, the value is still considerably far away from zero.

The low R^2 values for the emerging markets and especially for China and Russia may call for a discussion of the selection of the variables. Brazil and Mexico performed rather well in this regard, as their R^2 values are practically identical to Germany and Japan on a country level for both models. This similarity indicates that the selection of variables is fitting in the sense that the model provides similar results using the same independent variables for data sorted in comparable ways as has been done for the used data sets. For Russia and China, however, it is possible in this instance that other economic factors outside of these variables exist, which have a reducing effect on R^2 values. Potentially, the economic framework and assets included in these datasets could have such an effect. For example, the Chinese government backs a majority of economically strong companies by ownership in country blue chip-level assets and employs a mixture of free market orientation as well as economic planning. This includes industrial policies and strategic five-year plans. Rigid influence of this nature can influence the movement of such assets and may detach them from the assumed influence-free market behavior. A similar case exists for Russia where a mixture of free-market framework and government-led economic policies exists. The economic behavior of companies in such environments may not match with the assumptions taken in the researched models. One needs to remember that the independent variables from both the Fama French three and five-factor models reflect market capitalization, investment behavior, profitability, size, and value of companies in an efficient and self-regulating market. In markets like Russia and China, these factors may not necessarily follow the same rules and could potentially introduce effects, which lower the explanatory power of the regression returns of the underlying models.

In conclusion, the results from the calculations above have shown that the application of the Fama French five-factor model does not provide superior results to the application of the three-factor model in the analysis of macroeconomic and company-specific levels of data related to the COVID-19 pandemic. Certain indications are available that an introduction of additional factors may produce improved results, which would allow a better assessment of the available data from the COVID-19 pandemic, but the overall results show that the currently available factors are apparently insufficient in explaining these results in a valid manner. Our results are in line with previous tests of the Fama French multifactor models for market anomalies [2,3]. Consequently, the thesis that the use of a model, which employs further factors automatically yields better or more reliable results must be rejected at this point.

6. Conclusions

At the current moment, only the study by Kostin, Runge, and Adams from 2021 analyzes the economic effects of pandemics via multi-factor asset pricing models. Further research in this field is not available, which is also rooted in the fact that pandemics of this magnitude have not been seen before in a similar way. Motivated by the market frictions caused by crisis events [27], such as the GFC or the COVID-19 pandemic, this study challenges the validity of the Fama French five-factor model. This study provides novel insights in this field by adding results from the analysis via an additional multi-factor asset-pricing model, which may be used as a basis to develop more suitable asset-pricing models for the analysis of similar situations. This would be useful as the calculated results have revealed that there must be other factors besides the market beta and the Fama French-specific size, value, profitability, and investment pattern factors to explain the return development of underlying assets during a crisis such as the pandemic.

The authors suggest that the suitability of the current multi-factor asset-pricing models is limited due to their strong company-specific focus. Seeing that pandemics are global events, affecting economies on a macroeconomic level, research using a model focusing on more macroeconomic factors could prove to be beneficial. As Kostin, Runge, and Adams [2] have already suggested, the use of the Arbitrage Pricing Model as described by Ross [33] could be a reasonable approach as it uses a linear relationship between asset returns and a set of self-selected macroeconomic variables. Applying it may yield deeper insights into the determining factors of asset returns in pandemic situations. However, it must be mentioned that this model is significantly more complex than the pre-defined Fama French multi-factor models and requires a much higher effort to define determining asset-pricing factors upfront instead of using the predetermined variables from both the Fama French three and Fama French five-factor models.

Our study exhibits several limitations. First, by testing the Fama French multi-factor models empirically, our work is subject to all to the inherent limitations of these models. As outlined in Section 2, by being based on the CAPM, problems of a limited ability of empirical testing due to the restrictive assumptions, such as an unobservable market portfolio applies to our research as well [10]. Second, we acknowledge that the models under investigation in our study cannot capture variables related to irrational market behavior [34]. Being rooted in neoclassical theory, none of the factors in the Fama French models account for human investment behavior. Psychological investment biases may affect markets especially around crisis events. Herding, loss aversion, or decision-making based on emotional tensions such as excitement, fear, or anxiety may lead to capital markets not efficiently incorporating all available information into asset prices [35]. Consequently, our findings could be limited to an environment that exhibits efficient capital markets.

Author Contributions: Conceptualization, K.B.K., P.R.; methodology, K.B.K., P.R.; validation, K.B.K., P.R. and M.C.; formal analysis, K.B.K.; investigation, P.R.; resources, M.C.; data curation, K.B.K., P.R.; writing—original draft preparation, K.B.K., P.R.; writing—review and editing, K.B.K., P.R. and M.C.; visualization, K.B.K., P.R.; supervision, M.C.; project administration, M.C.; funding acquisition, M.C. All authors have read and agreed to the published version of the manuscript.

Funding: The article processing charge was funded by the Baden-Wuerttemberg Ministry of Science, Research and Art in the funding program Open Access Publishing.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Plotnikov, V.; Golovko, M.; Fedotova, G.V.; Rukinov, M. Digital Economy: Complexity and Variety vs. Rationality: Ensuring National Economic Security through Institutional Regulation of the Shadow Economy. In *Digital Economy: Complexity and Variety vs. Rationality. ISC 2019. Lecture Notes in Networks and Systems*; Popkova, E., Sergi, B., Eds.; Springer: Cham, Switzerland, 2019; Volume 3, pp. 342–351.
2. Kostin, K.; Runge, P.; Adams, R. Investment Strategies in Pandemic Situations: An Analysis and Comparison of Prospective Returns between Developed and Undeveloped Countries. *Strateg. Manag. J.* **2020**, *26*, 34–52.
3. Blitz, D.; Vidojevic, M. The profitability of low-volatility. *J. Empir. Financ.* **2017**, *43*, 33–42. [CrossRef]
4. Blitz, D.; Hanauer, M.X.; Vidojevic, M.; Van Vliet, P. Five Concerns with the Five-Factor Model. *J. Portf. Manag.* **2018**, *44*, 71–78. [CrossRef]
5. Sharpe, W. Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. *J. Financ.* **1964**, *19*, 436–438.
6. Lintner, K. The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *Rev. Econ. Stat.* **1965**, *47*, 13–37. [CrossRef]
7. Mossin, J. Equilibrium in a Capital Asset Market. *Econometrica* **1966**, *34*, 768–783. [CrossRef]
8. Black, F.; Jensen, M.C.; Scholes, M. The Capital Asset Pricing Model: Some Empirical Tests. In *Studies in the Theory of Capital Markets*; Jensen, M.C., Ed.; Praeger: New York, NY, USA, 1972; pp. 79–121.
9. Fama, E.; French, K. The Capital Asset Pricing Model: Theory and Evidence. *J. Econ. Perspect.* **2004**, *18*, 25–46. [CrossRef]
10. Roll, R. A Critique of The Asset Pricing Theory's Tests. *J. Financ. Econ.* **1977**, *4*, 129–176. [CrossRef]
11. Belen, B. The Use of CAPM and Fama French Three-Factor Model: Portfolios Selection. *Public Munic. Financ.* **2012**, *1*, 61–70.
12. Banz, R. The Relationship between Return and Market Value of Common Stocks. *J. Financ. Econ.* **1981**, *9*, 3–18. [CrossRef]
13. Litzenberger, R.; Ramaswamy, K. The effect of personal taxes and dividends on capital asset prices: Theory and empirical evidence. *J. Financ. Econ.* **1979**, *7*, 163–195. [CrossRef]
14. Basu, S. Investment performance of common stocks in relation to their price-earnings ratios. A test of market efficiency. *J. Financ.* **1977**, *32*, 663–682. [CrossRef]
15. Fama, E.; French, K. Common Risk Factors in the Returns on Stocks and Bonds. *J. Financ. Econ.* **1993**, *33*, 3–56. [CrossRef]
16. Fama, E.; French, K. Multifactor Explanations of Asset Pricing Anomalies. *J. Financ.* **1996**, *51*, 55–84. [CrossRef]
17. Fama, E.; French, K. Value versus Growth: The International Evidence. *J. Financ.* **1998**, *53*, 1975–1999. [CrossRef]
18. Belyh, A. The Definitive Guide to Fama French Three-Factor Model. Cleverism. 2019. Available online: https://www.cleverism.com/fama-french-three-factor-model-guide/ (accessed on 31 December 2021).
19. Fama, E.; French, K. A Five Factor Asset Pricing Model. *J. Financ. Econ.* **2015**, *116*, 1–22. [CrossRef]
20. Arnold, G.; Lewis, D. *Corporate Financial Management*, 6th ed.; Pearson Education: Harlow, UK, 2019; Chapter 3; p. 307. ISBN 9781292140445.
21. Fama, E.; French, K. Dissecting Anomalies with a Five-Factor Model. *Rev. Financ. Stud.* **2016**, *29*, 69–103. [CrossRef]
22. Fama, E.; French, K. Dissecting Anomalies. *J. Financ.* **2008**, *63*, 1653–1678. [CrossRef]
23. Racicot, F.E.; Rentz, W. Testing Fama-French's New Five Factor Asset Pricing Model: Evidence from Robust Instruments. *Appl. Econ. Lett.* **2016**, *23*, 444–448. [CrossRef]
24. Racicot, F.E. Engineering Robust Instruments for GMM Estimation of Panel Data Regression Models with Errors in Variables: A Note. *Appl. Econ.* **2015**, *47*, 981–989. [CrossRef]
25. Racicot, F.E.; Rentz, W.; Tessier, D.; Théoret, R. The Conditional Fama-French Model and Endogenous Illiquidity: A Robust Variables Test. *PLoS ONE* **2019**, *14*, e0221599. [CrossRef]
26. De Carvalho, G.A.; Amaral, H.F.; Pinheiro, J.L.; Correia, L.F. Pricing of Liquidity Risk: New Evidence from the Latin American Emerging Stock Markets. *Emerg. Mark. Financ. Trade* **2022**, *58*, 398–416. [CrossRef]
27. Miss, S.; Charifzadeh, M.; Herberger, T.A. Revisiting the Monday effect: A replication study for the German stock market. *Manag. Rev. Q.* **2020**, *70*, 257–273. [CrossRef]
28. Gibbons, M.; Ross, S.; Shanken, J. A Test of the Efficiency of a Given Portfolio. *Econometrica* **1989**, *57*, 1121–1152. [CrossRef]
29. Cakici, N.; Fabozzi, F.; Tan, S. Size, Value, and Momentum in Emerging Market Stock Returns. *Emerg. Mark. Rev.* **2013**, *16*, 46–65. [CrossRef]
30. Affleck-Graves, J.; McDonald, B. Nonnormalities and Tests of Asset Pricing. *J. Financ.* **1989**, *44*, 889–908. [CrossRef]
31. Griffin, J.; Kelly, P.; Nardari, F. Do Market Efficiency Measures Yield Correct Inferences? A Comparison of Developed and Emerging Markets. *Rev. Financ. Stud.* **2010**, *23*, 3225–3277. [CrossRef]
32. Zikmund, W.; Babin, B.; Carr, J.; Griffin, M. *Business Research Methods*, 9th ed.; Cengage Learning: Mason, OH, USA, 2013; Chapter 23; p. 51. ISBN 978-1111826925.
33. Ross, S. The Arbitrage Theory of Capital Asset Pricing. *J. Econ. Theory* **1976**, *13*, 341–360. [CrossRef]
34. Kahneman, D. New challenges to the rationality assumption. *J. Inst. Theor. Econ.* **1994**, *150*, 43–56.
35. Benartzi, S.; Thaler, R.H. Myopic loss-aversion and the equity premium puzzle. *Q. J. Econ.* **1995**, *110*, 75–92. [CrossRef]