mathematics

Article

Validity of the Fama-French Three- and Five-Factor Models in Crisis Settings at the Example of Select Energy-Sector Companies during the COVID-19 Pandemic

Konstantin B. Kostin [1,*], Philippe Runge [2] and Leyla E. Mamedova [1]

1 World-Class Research Center "Advanced Digital Technologies", State Marine Technical University, 190121 Saint-Petersburg, Russia
2 Graduate School, Nordakademie, 22767 Hamburg, Germany
* Correspondence: kost_kos@mail.ru; Tel.: +7-921-655-21-59

Abstract: This study empirically analyzes return data from select energy companies in developed and emerging markets using the Fama-French three- and five-factor asset-pricing models in crisis settings. It researches whether these models are suitable to produce meaningful return data in challenging economic circumstances. We use panel data covering 12 of the largest globally-operating energy companies from Russia, China, the US, the EU, and Saudi Arabia, covering a period between 2000 and 2022. The results undermine the general notion that the usage of available multi-factor asset-pricing models automatically yields meaningful data in all economic situations. The study reiterates the need to reconsider the assumption that the addition of more company-specific factors to regression models automatically yields better results. This study contributes to the existing literature by broadening this research area. It is the first study to specifically analyze the performance of companies from the energy sector in a crisis like the COVID-19 pandemic with the help of the Fama-French three- and five-factor models.

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

MSC: 91-10

check for updates

Citation: Kostin, K.B.; Runge, P.; Mamedova, L.E. Validity of the Fama-French Three- and Five-Factor Models in Crisis Settings at the Example of Select Energy-Sector Companies during the COVID-19 Pandemic. *Mathematics* **2023**, *11*, 49. https://doi.org/10.3390/math11010049

Academic Editor: Vladimir A. Plotnikov

Received: 15 November 2022
Revised: 13 December 2022
Accepted: 19 December 2022
Published: 23 December 2022

1. Introduction

Crises of varying magnitude have been a recurring phenomenon in the past decades. In most cases, the effects of these crises have been detrimental to the markets in which they occurred, be they at economic, political, or societal levels. Most of these events affected only individual countries and the nations bordering them, such as the Russian Financial Crisis (1998) or the isolated financial crisis of Iceland (2008–2010). However, some of these events prove so grave and devastating that markets on a global scale are affected. Examples of such catastrophic events are the Dot-com Bubble (2001), the Global Financial Crisis in line with the Global Recession (2007–2010), or the European Debt Crisis (2009 to late 2010s). One factor that connects these events is a similarity in their development. Specifically, they spread into other markets relatively slowly, showing effects in regions outside their points of origin after months or sometimes years. In contrast to this development pattern, another crisis has emerged where the distribution and economic damage were visible virtually immediately. This event was the onset of the COVID-19 pandemic in late 2019, which started as an endemic outbreak of an airborne virus strain, SARS-CoV-2, which showed very high potential to infect the respiratory organs in humans. Because of this feature and due to a strongly-interconnected global economic setup, this virus quickly spread to every significant economic market on the globe. At the time of its detection, it was considered one of the largest threats to healthcare systems on a global scale due to its route of transmission and severe levels of contagion. Additionally, it became a global health issue as it was not only able to infiltrate the respiratory tract easily, but it also inflicted severe damage to other organs and triggered massive immune reactions in the bodies of infected patients. As Kostin, Runge, and Adams [1] explain, the greatest threat displayed by this virus, economically speaking, was its attack on the very nature of economic continuity: the interaction between humans in conjunction with stable health levels of the population. During the timespan of the pandemic from late 2019 until the present, substantial amounts of the global workforce were repeatedly required to work from home, shopping was partially prohibited due to governmental actions against the spread of COVID-19, and most leisure activity was forced to be reduced to an absolute minimum. The consequences of these actions quickly showed themselves on a global scale. A wide range of businesses were forced to shut down globally to reduce contact between individuals on a large scale, notably the food service industry, entertainment businesses, and retail stores. In short, the outbreak of the COVID-19 pandemic rapidly disrupted the global supply chain and economy; eventually, it also resulted in a dramatic transformation in energy markets [2,3]. Additional effects included port closures, rising unemployment, and significant reduction of industry revenue and profit margins [4]. Moreover, the novel coronavirus pandemic has significantly affected global financial markets, as stock markets display patterns that are clearly different from those that were observed before and have been observed after the COVID-19 outbreak [5].

While several studies have been produced to research the effect of the COVID-19 pandemic on whole sectors, analyses on specific companies based on their sector affiliation are rare, and particularly not with the help of multi-factor asset pricing models in a crisis setting. Based on the prior work of Kostin, Runge, and Adams [1] and Kostin, Runge, and Charifzadeh [6], the authors of this study aim to research the following hypothesis:

- The Fama-French three- and five-factor models are unable to produce meaningful results in a crisis setting where the traditional setting of an efficient, self-regulating market is deeply disturbed.

The authors of this study decided to use data of select leading energy sector companies from developed and emerging markets. The global changes which are affecting countries at the moment act as a 'censor' of modern energy relations, and energy market development strategies in general. The development of the energy market is no longer considered in terms of its efficiency but more in terms of its survivability under the influence of external environmental factors and its ability to maintain an acceptable level of energy safety [7]. As this sector has been affected relatively severely by the COVID-19 pandemic, the authors believe it is a viable data source for a meaningful test of the above hypothesis.

The remainder of this study is structured as follows. Section 2 provides a literature review, outlining background information on the rationale for using energy companies in this study, information on the employed asset-pricing models, and the main criticisms they attract. Section 3 shows the data and methods of our analysis. Sections 4 and 5 present the results of the analysis and the subsequent discussion. Section 6 provides a conclusion and outlines notable limitations of this study.

2. Literature Review

2.1. Energy Sector and Impact of COVID-19 Pandemic

In a globalized economy, energy has become one of the—if not the most—important factors enabling the smooth and reliable continuity of most businesses worldwide. It comes as no surprise that, as of 2020, energy companies made up six of the ten largest companies by revenue [8]. The constant supply of energy, be it in the form of electricity, heat, or fossil fuels, is so crucial that an interruption can have detrimental effects, both from a reduction of supply and a reduction in demand. In the first months of 2020, the International Energy Agency (IEA) [4] noted that countries which went into lockdown saw a reduction in energy demand of between 18–25% per week, on average. Additionally, the IEA [8] discovered that the demand for electricity fell by 20% in countries where lockdowns were imposed. The IEA [9] also reported an extraordinary decline in mobility, where a 57% decline was observed. This number is supported in more granular detail by Du et al. [10], who mentioned a 65% reduction of mobility in the US. Szczygielski et al. [11] found the energy sector was hit especially strongly by COVID-19, particularly from increased market volatility having a negative effect on fossil fuel prices. Rokicki et al. [12] concluded that, while demand for energy dropped in terms of mobility and production, household demand for energy increased significantly. Hoang et al. [13] contend that COVID-19 may have been the catalyst for the decline of the entire fossil-fuel energy sector.

To no great surprise, COVID-19 has not only impacted traditional, fossil-fuel-based energy production processes, but also the renewable energy sector. Hoang et al. [13] outline that solar and wind power plant construction has seen an 8–12% reduction in 2020 alone due to supply-chain interruptions in related production plants worldwide [2,3,5,7]. In this regard, the energy sector may be positioned in a complex and uncertain situation with a difficult outlook on its future due to the pandemic. The analyzed literature gives sufficient reason to assume that a crisis of the magnitude of COVID-19 has a severely destructive influence on the energy sector, considerably higher than on other economic sectors. As such, the whole sector is an ideal candidate for analysis where meaningful results on its performance can be generated by the application of asset-pricing models which have not been tested in such cataclysmic events.

2.2. Criticism of Multi-Factor Asset Pricing Models

As already mentioned above, this study will assess the validity of multi-factor asset-pricing models in crisis settings as the authors believe the available models—most prominently the Fama-French three- and five-factor models—are unsuitable for their use in settings of erratic economic circumstances. To understand this hypothesis in better detail, one must comprehend the fundamental basis of these models, in order to grasp their inherent flaws. Both the Fama-French three- and five-factor models are based on the Capital Asset Pricing Model (CAPM) as introduced by Sharpe [14], Lintner [15], and Mossin [16] around the same time in the 1960s. CAPM is fundamentally based on the assumption that a linear relationship exists between the market risk factor and the expected return of any given stock. The model quickly developed into a prominent and well-renowned approach to asset pricing as it was simple and easy to apply. However, it also received widespread criticism regarding its actual applicability, due its unrealistic assumptions. Roll [17] argues this model is invalid as CAPM implies market portfolio efficiency, a concept considered elusive and impossible to test in a real-world setting as outlined by Fama and French [18]. Roll [17] explains that the market portfolio's composition cannot be determined, making it factually impossible to fully test CAPM. In an effort to improve CAPM's performance and bring asset-pricing calculations closer to a realistic level, Fama and French [19] introduced an extended model which adds two additional factors to CAPM's market beta. Fama and French [19] managed to demonstrate in this model that smaller companies perform better than larger companies by producing higher returns, and that performance is superior when a company holds large assets compared to its relative share market valuation, when considered against a company holding smaller assets compared to its relative share market valuation. Belyh [20] supports this finding by stating that the three-factor model was apparently able to explain 90% of a portfolio's return variations, while CAPM only manages to explain approximately 70% of a portfolio's return variations. However, the model did not approach the CAPM-specific issues and is therefore also fundamentally flawed in its own setup. In a recent study that supported the authors' contention these models are problematic in crisis environment applications, Kostin, Runge, and Adams [1] applied the model using company- and country-specific data from the COVID-19 pandemic and were able to demonstrate the model showed surprisingly poor performance. The notion that multi-factor asset-pricing models do not perform as expected in turbulent settings is also backed up by a study from Kostin, Runge, and Charifzadeh [6] who assessed whether the Fama-French five-factor model from 2015 [21] performed better compared to their three-factor model in a similar setting as Kostin, Runge, and Adams [1], but the results of their study concluded the five-factor model also performed poorly in the same crisis setup. This raises the question whether the currently available multi-factor asset-pricing models are valid at all in their widespread application for asset return calculation. Additional criticism was published shortly after the creation of the five-factor model. Blitz et al. [22] concluded in their study that major issues exist with the five-factor model. Most notably, they underlined [22] that the model is as invalid as its predecessor, the three-factor model, as it is still only an extension of CAPM's basic equation and thereby inherently flawed as a result of CAPM's unrealistic assumptions. Additionally, Blitz et al. [22] point out that the model's additional factors are no longer based on risk, as per the previous factors, but on quality-specific points. Arnold and Lewis [23] outline that Fama and French were able to demonstrate superior share returns of companies with higher profit-to-net-asset ratios, which was not previously included in the three-factor model. Fama and French noticed that companies with small changes to their total assets performed better than companies with large changes to their total assets. Blitz et al. [22] conclude in this regard that risk-based investors would expect low-profitability companies with increased risk to outperform high-profitability companies with reduced risk and not the other way around as suggested by Fama and French's five-factor model. Most interestingly, Blitz et al. [22] add to this criticism, noting that by leading the model away from a risk-based approach toward ambiguous quality-specific factors, the model may simply be extended with factors until it eventually fits the purpose sufficiently well. Further doubt is also presented by Racicot et al. [24] in terms of the model's mathematical foundation. Racicot et al. [24] determined that the five-factor model only performs well if a standard econometric estimator like an Ordinary Least Squares (OLS) estimation is used. Racicot et al. [25] tested their own results by developing an analysis method for such multi-factor models by using a Generalized Method of Moments (GMM) approach. Racicot [25] was subsequently able to determine that the explanatory power of the Fama-French five-factor model was significantly reduced this way, compared to using only an OLS-based approach.

Looking at all these valid points of criticism, one can conclude that the validity of both the Fama-French three- and five-factor models is strongly limited. The notion that these models can practically be used for any setting must accordingly be challenged. Consequently, this study aims to provide empirical evidence of the reduced validity of these models in crisis settings like the COVID-19 pandemic.

3. Methods

3.1. Model

This study uses the Fama-French three- and five-factor models to calculate the cost of equity from the chosen companies' available market data. The regression equation for the three-factor model is as follows:

$$\mathrm{R_{i,t} - R_{Ft} = a_i + \beta_1 (R_{Mt} - R_{Ft}) + \beta_2 SMB_t + \beta_3 HML_t} + \varepsilon_{i,t} \tag{1}$$

in which $\mathrm{R_{i,t}}$ is the return of a portfolio i for month t, $\mathrm{R_{Ft}}$ is the risk-free rate, ai denotes the intercept value, β_{123} outlines the factor coefficient, $\mathrm{SMB_t}$ (Small Minus Big) is the variable capturing size, i.e., the difference between returns of diversified portfolios of small and big stocks, $\mathrm{HML_t}$ (High Minus Low) is the difference between the return on diversified portfolios of high and low B/M stocks, and $\mathrm{e_{i,t}}$ denotes the error term of a portfolio i for a month t. The regression equation for the five-factor model is as follows:

$$\mathrm{R_{i,t} - R_{Ft} = a_i + b_i (R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t} + \varepsilon_{i,t} \tag{2}$$

in which the equation from the three-factor model has been amended where $\mathrm{RMW_t}$ (Robust Minus Weak) is the difference between companies having robust and weak operating profitability, and $\mathrm{CMA_t}$ (Conservative minus Aggressive) is the difference between the return of companies investing conservatively and companies investing aggressively. As performed by

Kostin, Runge, and Adams [1], this study divided the cost of equity calculation into subgroups to facilitate the analysis of the models in the given dataset. The sub-categories are:

- Complete Data Period
- Global Financial Crisis Period
- COVID-19 Period

3.2. Test of Model Performance

As suggested by Gibbons, Ross, and Shanken [26], this study will use the GRS F-test statistic to evaluate the Fama-French three- and five-factor models' performance on the underlying datasets by testing that null H_0: $\alpha_i = 0$ jointly for all i. The GRS test is conducted by performing an OLS (Ordinary Least Squares) regression first. Afterwards, the intercept of the alphas is calculated. In the end, the test assesses whether the joint value of the alphas is zero. The equation for the GRS test statistic is constructed using the intercepts and error terms as outlined in Equations (1) and (2). Let $\alpha_i = (\alpha_1, \ldots, \alpha_n)$ and let $\varepsilon_i = (\varepsilon_1, \ldots, \varepsilon_n)$ be n-vectors, including the intercept values and error values from Equations (1) and (2). 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-statistic is given by the equation below:

$$F = \left(\frac{T}{N}\right)\left(\frac{T-N-L}{T-L-1}\right)\left[\frac{\hat{\alpha}'\hat{\sum}^{-1}\hat{\alpha}}{1+\overline{\mu}_L'\hat{\Omega}^{-1}\overline{\mu}_L}\right] \tag{3}$$

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 portfolios' covariance matrix.

Following H_0 that all regression intercepts are zero, the GRS test statistic expresses an F distribution with N and $T - L - 1$ degrees of freedom. The expectation would be that the application of the test will provide reliable insights into the capability of the multi-factor models to help explain the variations in returns for a given portfolio. Higher result values from the GRS test would indicate that the value of the combined intercepts deviates strongly from zero, meaning that the model's factors are insufficient in effectively explaining the variation of the portfolio's return. More precisely, a higher value of the GRS test statistic equals a higher joint alpha that deviates further from zero. Results of this kind would allow the conclusion of inadequate performance of the tested asset-pricing model.

As Kostin, Runge, and Charifzadeh [6] explain, the current literature suggests additional tests to cover concerns about non-normal and serially-autocorrelated errors. The most prominent test was proposed by Cakici, Fabozzi, and Tan [27], who applied a Generalized Method of Moments (GMM) in connection with the GRS test. However, this approach is not quite suitable for the use of panel data as undertaken in this study. Racicot et al. [24] have suggested a more fitting estimator in their study which specifically addresses panel data regressions. They base their approach [24] on higher moments as well as cumulants and were able to demonstrate that their estimator—together with the GMM method—can be used to construct a more reliable estimation than the GMM approach alone. As outlined earlier, Racicot et al. [24] used an augmented version of the Fama-French five-factor model. It is likely their approach may also work on the original five-factor version without augmentations as well as the three-factor version; for the three-factor model, this is mainly because it only consists of two fewer factors. Despite these arguments, the authors decided not to apply this approach as the GRS test appears to be sufficiently suitable to account for non-normal error terms. This rationale is supported by Affleck-Graves and McDonald [28], who outline that the GRS test is usually not sensitive to non-normal sample distributions, given the distributions are within typical levels of non-normality. Affleck-Graves and McDonald [28] further add the power of the GRS test can indeed be significantly misinterpreted, but only in instances where the levels of non-normality are also significant. Such instances usually occur for datasets of extensive size, often spanning several decades of data. Affleck-Graves and McDonald [28] state that it is difficult in such datasets to rule out the presence of periodic effects where a non-trivial deviation from normality could be explained. As the underlying dataset does not extend beyond a timeframe of 20 years, the authors consider there is no valid reason to assume a non-trivial deviation from normality where further validation of the data would be required.

3.3. Data

As mentioned earlier, this study aims to specifically assess the performance of select companies in the energy sector during the COVID-19 pandemic by applying the Fama-French three- and five-factor models. The authors employed stock data for select energy companies from both developed and emerging markets. Stock data used for this study was taken from Yahoo Finance. To allow sufficient robustness and comparability between the company data, the datasets have been limited to a range between January 2000 and April 2022. The cut-off limit denominates the timeframe in which most COVID-19 restrictions were lifted in the selected regions. The firms analyzed in this study are BP, Shell, Total Energies, ExxonMobil, Chevron, and Nextera for the developed markets, as well as Lukoil, Gazprom, Rosneft, Saudi Electricity, Sinopec, and China Petroleum for the emerging markets. Company-level stock data was not available prior to 2006 for Rosneft, prior to 2002 for Saudi Electricity, prior to October 2000 for Sinopec, and prior to April 2000 for Petrochina. Monetary information in the datasets was converted to US Dollar where necessary; excess returns were calculated using the one-month U.S. Treasury bill rate. Data before 2000 (where available) and after April 2022 has been excluded from the analysis.

We would like to note that the COVID-19 pandemic was not declared to be over while this study was being written, despite restrictions having been loosened or rescinded in many countries globally. New governmental restrictions and detrimental economic effects cannot be ruled out for the near future and may show additional effects on the results presented below once taken into consideration. Consequently, additional data will have to be used for future analyses of such effects on global markets, e.g., supply chain interruptions, resource scarcity, inflationary pressure, or trade sanctions and restrictions.

3.4. Implementation of Asset-Pricing Model Factors

In this study, the authors consider five different factors which are being used as explanatory values in the regression Equations (1) and (2). These coefficients are the market factor, SMB factor, HML factor, RMW factor, and CMA factor. The factor-specific data has been retrieved from French's data library, accessible at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html (accessed on 6 October 2022). The factors of the developed markets include data from 23 developed countries. The factors of the emerging markets are comprised of data from 26 emerging countries. Further information on the creation of the factors for both developed and emerging markets can be found in French's data library at the following location: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_5developed.html (accessed on 7 October 2022), and https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_5emerging.html (accessed 6 October 2022).

4. Results

This section presents the empirical results of this study.

4.1. Analysis Results for the Fama-French Three-Factor Model

As outlined by Kostin, Runge, and Charifzadeh [6], a mutual agreement exists in the available literature that an asset-pricing model performs well if the intercept value of its results is as close to zero as possible. Fama and French [19] further this point by stating that asset pricing models only support their results if there is no possibility to group assets into portfolios in such a way that their intercept values are different from zero. As outlined in Table 1, the three-factor model is successful in producing intercept values of this nature as they are all remarkably close to zero for all selected companies.

Table 1. Fama-French Three-Factor Regression Results for Leading Energy Companies, * $p < 0.05$; standard deviation on mean values in brackets.

Company	α	t(α)	β	SMB	HML	R^2 (Adjusted)
Lukoil	0.0001	0.02	1.1 *	−0.27	0.34	0.29
Rosneft	0.01	0.81	0.42 *	0.28	0.20	0.03
Gazprom	0.29	1.56	3.06	0.78	−7.52	0.01
Saudi Electricity	0.0031	0.63	0.19 *	−0.02	0.26	0.03
Sinopec	−0.01	−1.92	−0.02	−0.19	0.79	0.02
Petrochina	−0.004	−0.66	−0.15	0.51	0.23	0.02
ExxonMobil	0.0007	0.21	0.70 *	−0.23	0.71 *	0.34
Chevron	0.0027	0.85	0.89 *	−0.22	0.76	0.43
Nextera	0.01 *	3.47	0.43 *	−0.51 *	0.08 *	0.14
BP	−0.0039	−1.04	1.01 *	−0.17	0.78 *	0.40
Shell	−0.0019	−0.60	0.95 *	−0.06	0.76 *	0.44
Total Energies	0.0002	0.06	0.98 *	−0.10	0.66 *	0.48
GRS Developed: 8.72 *						Average R^2 Developed: 0.37 (0.11)
GRS p-value: 2.820×10^{-9}						
GRS Emerging: 5.47 *						Average R^2 Emerging: 0.07
GRS p-value: 1.394×10^{-5}						(0.37)

α denotes the intercept value. T(α) is the T statistic of α, denoting the linear relationship between the dependent and independent variables, and β constitutes the risk-free rate. One of the six alpha values for the developed market companies was statistically significant at the 0.05 level, while none of the alpha values for the emerging market companies was statistically significant. All β values of the developed market companies were statistically significant at the 0.05 level, while three β values of the emerging market companies were statistically significant. One SMB value was significant at the 0.05 level for the developed market companies, while none of the SMB values for the emerging market companies were statistically significant. 5 HML values were significant at the 0.05 level for the developed market companies. No HML values were statistically significant for the emerging market companies. The three-factor model produced surprisingly erratic R^2 values for the emerging market companies, with an average R^2 of 0.07. The average R^2 for the developed market companies, in contrast, was 0.37. The GRS test statistic for the emerging market companies was 5.47 at the 0.05 level. The GRS test statistic for the developed market companies was 8.72 at the 0.05 level.

4.2. Analysis Results for the Fama-French Five-Factor Model

Table 2 outlines the results of the analysis of the selected companies using the Fama-French Five-Factor model. As in Table 1, α denotes the intercept value. T(α) is the T statistic of α, denoting the linear relationship between the dependent and independent variables, and β constitutes the risk-free rate. One of the six alpha values for the developed market companies was statistically significant at the 0.05 level. Also, one of the six alpha values for the emerging market companies was statistically significant at the 0.05 level. All β values of the developed market companies were statistically significant at the 0.05 level. Two β values of the emerging market companies were statistically significant at the 0.05 level. For both the developed and emerging market companies, none of the SMB values were statistically significant at the 0.05 level. Five of the HML values were statistically significant at the 0.05 level for the developed market companies, while only one HML value was statistically significant at the 0.05 level for the emerging market companies. For both the developed and emerging market companies, one out of six RMW values was statistically significant at the 0.05 level. Similarly, only one out of six CMA values was statistically significant at the 0.05 level for both the developed and emerging market companies. The average R^2 was 0.39 for the developed market companies and 0.09 for the emerging market companies. The GRS test statistic was 7.88 at the 0.05 level for the emerging market companies. The GRS test statistic for the developed market companies was 3.73 at the 0.05 level.

Table 2. Fama-French Five-Factor Regression Results for Leading Energy Companies, * $p < 0.05$; standard deviation on mean values in brackets.

Company	α	t(α)	β	SMB	HML	RMW	CMA	R^2 (Adjusted)
Lukoil	0.003	0.46	0.98 *	−0.39	0.42	−0.51	−0.58	0.30
Rosneft	0.02 *	2.15	−0.12	−0.06	0.79	−2.35 *	−2.1 *	0.10
Gazprom	0.26	1.25	2.78	1.31	−2.05	11.03	−7.80	0.01
Saudi Electricity	0.003	0.52	0.18	−0.01	0.33	0.13	−0.08	0.04
Sinopec	−0.01	−1.64	−0.11	−0.24	0.99 *	−0.15	−0.50	0.01
Petrochina	−0.004	−0.55	0.26 *	0.48	0.55	0.11	−0.79	0.02
ExxonMobil	−0.0009	0.28	0.79 *	−0.18	0.41 *	0.05	0.59 *	0.35
Chevron	0.0002	0.05	0.98 *	−0.11	0.60 *	0.41	0.30	0.44
Nextera	0.01 *	2.12	0.56 *	−0.33	−0.10	0.77 *	0.31	0.18
BP	−0.004	−1.14	1.04 *	−0.16	0.68 *	0.03	0.19	0.41
Shell	−0.002	−0.75	0.99 *	−0.05	0.61 *	−0.02	0.30	0.46
Total Energies	−0.0004	−0.13	1.0 *	−0.07	0.62 *	0.10	0.06	0.48
GRS Developed: 3.73 *								Average R^2 Dev: 0.39 (0.11)
GRS p-value: 1.11×10^{-3}								
GRS Emerging: 7.88 *								Average R^2 Em: 0.09 (0.03)
GRS p-value: 2.55×10^{-8}								

4.3. Cost-of-Equity Results for Fama-French Three-Factor Model

Table 3 outlines the cost of equity calculation results for the selected energy companies from developed and emerging markets, based on the Fama-French three-factor model. On average, the cost of equity for the developed market companies was 8.1% during the full data period. During the COVID-19 period, the average cost of equity for the developed market companies rose to 11.39%. During the GFC period, the average cost of equity for the developed market companies was 0.11%. For the emerging market companies, the average cost of equity for the full data period was 6.3%. The average cost of equity during the COVID-19 period was 83.54% for the emerging market companies. The average cost of equity during the GFC period was 5.61% for the emerging market companies. It must be noted—as visible in Table 3—that the average cost of equity during the COVID-19 period is significantly skewed by the cost-of-equity result for Gazprom. Further research would be required to determine why this company's cost of equity value deviated so significantly from the results of the other companies in this dataset.

4.4. Cost-of-Equity Results for Fama-French Five-Factor Model

Table 4 outlines the cost of equity calculation results for the selected energy companies from developed and emerging markets, based on the Fama-French five-factor model. On average, the cost of equity during the full data period for the developed market companies was 10.12%. The average cost of equity for the developed market companies during the COVID-19 period was 9.92%. The average cost of equity for the developed market companies was 11.81% during the GFC. In contrast, the average cost of equity for the emerging market companies was 4.1% during the full data period. The average cost of equity for the emerging market companies was 31.35% during the COVID-19 period. The average cost of equity for the emerging market companies was −1.99% during the GFC period. As with the results for the three-factor model, it must be noted that the COVID-19 results are significantly skewed for the five-factor model results by Gazprom's cost-of-equity result. As already mentioned, further research would be needed to identify the reason for this deviation.

Table 3. Fama-French Three-Factor Cost of Equity Calculation for Leading Energy Companies in percent; standard deviation in brackets.

Company	Full Data Period	COVID-19	GFC
Lukoil	8.80 (2.35)	11.30 (2.36)	1.93 (0.33)
Rosneft	5.03 (1.7)	2.24 (0.29)	−4.01 (0.33)
Gazprom	−43.51 (12.25)	394.10 (39.29)	6.13 (2.38)
Saudi Electricity	5.10 (2.77)	7.17 (1.21)	0.35 (0.13)
Sinopec	9.53 (1.2)	5.37 (0.99)	1.09 (0.28)
Petrochina	5.53 (1.33)	−1.75 (0.22)	8.53 (2.43)
ExxonMobil	7.77 (2.19)	10.46 (0.83)	0.33 (0.32)
Chevron	9.00 (1.63)	14.96 (3.39)	−0.16 (0.02)
Nextera	3.20 (2.43)	8.31 (1.25)	0.58 (0.2)
Shell	9.60 (1.16)	9.17 (2.49)	0.68 (0.15)
BP	9.77 (1.23)	11.14 (1.44)	−1.14 (0.39)
Total Energies	9.27 (1.11)	14.29 (2.39)	−0.05 (0.01)
Average Developed	8.10%	11.39%	0.11%
Average Emerging	6.30%	83.54%	5.61%

Table 4. Fama-French Five-Factor Cost of Equity Calculation for Leading Energy Companies in percent; standard deviation in brackets.

Company	Full Data Period	COVID-19	GFC
Lukoil	12.62 (2.27)	8.80 (0.31)	11.93 (0.54)
Rosneft	−9.87 (1.2)	−15.23 (3.32)	−24.71 (6.34)
Gazprom	8.80 (2.28)	178.69 (19.31)	15.19 (5.29)
Saudi Electricity	5.54 (1.34)	6.00 (0.34)	6.64 (0.21)
Sinopec	7.07 (2.31)	4.65 (0.39)	0.47 0.35)
Petrochina	4.28 (0.8)	2.66 (0.31)	−11.47 (0.34)
ExxonMobil	9.67 (1.12)	10.46 (2.38)	11.64 (2.28)
Chevron	12.02 (3.25)	14.65 (3.33)	15.54 (4.27)
Nextera	8.17 (2.15)	8.10 (1.37)	−6.07 (1.42)
Shell	10.36 (3.13)	6.12 (0.52)	17.57 (4.62)
BP	10.49 (2.11)	7.26 (0.46)	21.41 (6.34)
Total Energies	9.98 (1.13)	12.92 (3.39)	10.78 (1.2)
Average Developed	10.12	9.92	11.81
Average Emerging	4.10	31.35	−1.99

Additionally, it must be mentioned that several of the cost-of-equity results showed negative values in both researched models. These values resulted from significantly large arrays of negative return data for assets during the COVID-19 pandemic as well as the GFC, and should be viewed with a high degree of caution. These results indicate significant distorting effects on the underlying economic circumstances of the observed companies, which pushed their cost of equity into a negative range.

5. Discussion

Tables 1 and 2 above outline that the Fama-French three- and five-factor model have not returned results as expected by the authors. As an initial measure of the performance of the models, the authors have assessed the R^2 values provided by the regression analyses for all companies and both models. The results deviate strongly between the developed and emerging market companies but are quite similar within the datasets of the developed market companies and emerging market companies, with the emerging market companies showing an R^2 between 0.01 and <0.31 in both models, and the developed market companies showing an R^2 between 0.14 and <0.48 in both models. Although there is no documented consensus on the classification of adequacy of fit of a model via the R^2 value, a rough estimate on the value's meaning has been classified by Zikmund et al. [29]:

- $R < 0.3$ no or very weak effect
- $0.3 < R < 0.5$ weak effect
- $0.5 < R < 0.7$ moderate effect
- $R > 0.7$ strong effect

It is surprising to see that the regression results for the selected companies have shown poor size effects for both the developed and emerging market examples. The results for the developed market companies are only considered weak, while the results for the emerging market companies indicate there is almost no size effect of R^2, with values going as low as 0.01. Only Lukoil is a stronger outlier, at 0.3. This is already considerably disheartening, as both the independent variables from the Fama-French three- and five-factor models are apparently unable to explain the variation from 1% to 48% in the dependent variable. The significantly low R^2 for the emerging market companies may make a discussion on the selection of the variables for these countries necessary; in a certain way, this would also be true for the developed market companies as their R^2 is likewise not exactly perfect. The similarity of the results between both multi-factor models indicates that the choice of factors is not fitting well in the sense that the models provide similarly poor outcomes using the same independent variables for comparably-sorted data. It should particularly be noted that in the case of countries where the assessed companies are headquartered, there may be express economic factors which could have a seriously diminishing effect on the R^2 value of these models. For example, Kostin, Runge, and Charifzadeh [6] explain that China employs a mixture of free-market orientation and economic planning, as well as backing economically strong companies with blue-chip asset ownership. In these measures, strategic long-term plans and economic policies are included. Influence of this nature may also impact the movement of such assets and may decouple them from the movement of an influence-free market. A similar setting exists for Russia and Saudi Arabia, where mixtures of government-mandated policies and free-market orientation exist. The expectation for the economic behavior of companies in such markets may not be congruent with the assumptions forming the basis of the researched models. One must keep in mind that the factors used in both the Fama-French three- and five-factor models reflect the properties of companies in an efficient and fully-self-regulated market. This setting may likely not be available in countries like China, Russia, or Saudi Arabia, where the deviation from the rules of a self-regulated market may introduce factors that lower the explanatory power of the regression results in the researched models. Additionally, for both developed and emerging markets, significantly adverse changes to the economic environment like the COVID-19 pandemic may also introduce factors which exert a strong influence on the explanatory power of the traditional available factors and their underlying assumptions. Consequently, irrational asset movement for any market can prove an expected result. However, it is not possible to determine these factors with the researched models, simply due to the fact they do not allow for an addition or alteration of the factors in their established format.

Further doubt regarding the validity of the results from both models is introduced by the results of the GRS test statistic shown in Tables 1 and 2. The values for both markets, developed and emerging, strongly deviate from zero. These results suggest the models are insufficient in explaining the variations in the return data of the researched company data. As one can see, the GRS test result for the emerging market companies lies at 5.47 for the three-factor model and rises to 7.88 after the application of the five-factor model. For the developed market companies, the situation is a little different with the GRS test result reducing from 8.72 in the three-factor model to 3.73 in the five-factor model. The reduced value itself is still quite far from zero. As all GRS test values were statistically relevant, it becomes clear that H_0: $\alpha = 0$ for the Fama-French three-and five-factor models must be rejected at this point.

6. Conclusions

In summary, the calculation results have shown the applications of the Fama-French three- and five-factor models are limited in the underlying setting, as they do not provide reliable results in a company-specific setting which has been affected by significant crises such as the COVID-19 pandemic. The results also indicate the currently-available factors are insufficient for explaining crisis behavior of an underlying asset using models that do not incorporate the expectation of the occurrence of such crises. These results are in line with previous tests of the Fama-French multi-factor models for market anomalies [1,6]. Therefore, the thesis that the Fama-French three- and five-factor models are suitable assessment tools for asset performance in irrational crisis situations must be rejected.

At the current moment, there are no studies which exclusively examine the performance of energy-sector companies with the help of the Fama-French three- and five-factor models during specific crisis events like the COVID-19 pandemic. Relatable studies are only available with limited comparability such as Kostin, Runge, and Charifzadeh [6] and Kostin, Runge, and Adams [1], who only included a minimal number of such companies in their analyses. This study provides novel insights into this field as it generates multi-factor asset-pricing model-based results which can be used as a basis to develop improved asset-pricing models for future occurrences of similarly complex and distressing events. Doing so is necessary as the results of this study have also revealed there must be other factors than the market risk factor and the Fama-French-specific company factors which are able to explain the return development of underlying assets in crisis settings in a more reliable manner.

The authors suggest at this point that the suitability of the currently-available multi-factor asset-pricing models is limited for an application in crisis situations, as their focus is entirely company-centric. As Kostin, Runge, and Charifzadeh [6] specify, research focusing on more macro-economic factors could be fruitful, seeing that crisis events like the GFC or pandemics are affecting markets on a global scale. As Kostin, Runge, and Adams [1] have previously suggested, a model based on the Arbitrage Pricing Theory as suggested by Ross [30] could be a viable approach as it suggest a linear relationship between asset prices and self-determined macro-economic factors. Although this model is significantly more complex due to the necessity to determine factors upfront, it may yield more meaningful results in such settings where the current well-tried factor models meet their inherent limits. Additionally, further studies using data from the recent global inflation crisis using the underlying Fama-French three- and five-factor models could be conducted, especially in the energy sector, to compare the performance of this sector in both crisis settings. Studies of this nature may provide interesting insights on the impact of crises where the global economic setup is affected, compared to a crisis situation where energy companies may potentially be affected in a beneficial manner.

The authors acknowledge this study exhibits several limitations. Firstly, by using the Fama-French three-and five-factor models empirically, the results from this study are also subject to the same criticism and inherent limitations of these models. As explained in Section 2, both models are based on the CAPM and are therefore holding the same problem of a limited ability to conduct empirical testing due to problematic assumptions, such as the availability of the unobservable market portfolio. Additionally, as outlined by Kostin, Runge, and Charifzadeh [6], the models employed are unable to capture variables related to irrational market behavior. As Kostin, Runge, and Charifzadeh [6] explain, both models are deeply ingrained in neoclassical theory, thereby neglecting the influence of human behavior on investment decisions. There may be a greater array of influencing factors than purely economic ones, such as psychological biases, which may affect market behavior during crisis situations. Significant loss-aversion tendencies and the tendency for emotion-based decision-taking may not lead to capital markets incorporating the available information into asset pricing in an efficient manner [31]. Consequently, the findings of this study may only be appropriate in a setting where efficient markets are exhibited.

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

Funding: This research is partially funded by the Ministry of Science and Higher Education of the Russian Federation as part of the World-class Research Center program: Advanced Digital Technologies (contract No. 075-15-2022-312 dated 20 April 2022).

Data Availability Statement: Not applicable.

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

References

1. 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.
2. Ghabri, Y.; Ayadi, A.; Guesmi, K. Fossil energy and clean energy stock markets under COVID-19 pandemic. *Appl. Econ.* **2021**, *53*, 4962–4974. [CrossRef]
3. Shaikh, I. Impact of COVID-19 pandemic on the energy markets. *Econ. Chang. Restruct.* **2022**, *55*, 433–484. [CrossRef]
4. Drobot, E.V.; Drobot, E.; Makarov, I.; Petrenko, Y.; Koshebayeva, G. Relationship between Countries' Energy Indicators and the Indices of GVC Participation: The Case of APEC Member Economies. *Energies* **2022**, *15*, 1675. [CrossRef]
5. Wielechowski, M.; Czech, K. Companies' Stock Market Performance in the Time of COVID-19: Alternative Energy vs. Main Stock Market Sectors. *Energies* **2021**, *15*, 106. [CrossRef]
6. 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. [CrossRef]
7. Maksimtsev, I.A.; Kostin, K.B.; Berezovskaya, A.A. Modern Trends in Global Energy and Assessment of the Ever-Increasing Role of Digitalization. *Energies* **2022**, *15*, 8767. [CrossRef]
8. International Energy Agency (IEA). The COVID-19 Crisis is Causing the Biggest Fall in Global Energy Investment in History. Available online: https://www.iea.org/news/the-COVID-19-crisis-is-causing-the-biggest-fall-in-global-energy-investment-in-history (accessed on 8 October 2022).
9. International Energy Agency (IEA). Oil Market Report—April. 2020. Available online: https://www.iea.org/reports/oil-market-report-april-2020 (accessed on 9 October 2022).
10. Du, J.; Rakha, H.; Filali, F.; Eldardiry, H. COVID-19 Pandemic Impacts of Traffic System Delay, Fuel Consumption, and Emissions. *J. Transp. Sci. Technol.* **2021**, *10*, 184–196. [CrossRef]
11. Szczygielski, J.J.; Brzeszczynski, J.; Charteris, A.; Bwanya, P.R. The COVID-19 Storm and the Energy Sector: The Impact and Role of Uncertainty. *Energy Econ.* **2022**, *109*, 105258. [CrossRef]
12. Rokicki, T.; Jadczak, R.; Kucharski, A.; Bórawski, P.; Bełdycka-Bórawska, A.; Szeberényi, A.; Perkowska, A. Changes in Energy Consumption and Energy Intensity in EU Countries as a Result of the COVID-19 Pandemic by Sector and Area Economy. *Energies* **2022**, *15*, 6243. [CrossRef]
13. Hoang, A.T.; Nizetic, S.; Olcer, A.; Ong, H.; Chen, W.-H.; Chong, W.; Thomas, S.; Bandh, S.; Nguyen, X. Impacts of COVID-19 Pandemic on the Global Energy System and the Shift Progress to Renewable Energy: Opportunities, Challenges, and Policy Implications. *Energy Policy* **2021**, *154*, 112322. [CrossRef] [PubMed]
14. Sharpe, W. Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. *J. Financ.* **1964**, *19*, 436–438.
15. 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]
16. Mossin, J. Equilibrium in a Capital Asset Market. *Econometrica* **1966**, *34*, 768–783. [CrossRef]
17. Roll, R. A Critique of The Asset Pricing Theory's Tests. *J. Financ. Econ.* **1977**, *4*, 129–176. [CrossRef]
18. Fama, E.; French, K. The Capital Asset Pricing Model: Theory and Evidence. *J. Econ. Perspect.* **2004**, *18*, 25–46. [CrossRef]
19. Fama, E.; French, K. Common Risk Factors in the Returns on Stocks and Bonds. *J. Financ. Econ.* **1993**, *33*, 3–56. [CrossRef]
20. Belyh, A. *The Definitive Guide to Fama French Three-Factor Model*; Cleverism: Berlin, Germany, 2019. Available online: https://www.cleverism.com/fama-french-three-factor-model-guide/ (accessed on 10 October 2022).
21. Fama, E.; French, K. A Five Factor Asset Pricing Model. *J. Financ. Econ.* **2015**, *116*, 1–22. [CrossRef]
22. 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]
23. Arnold, G.; Lewis, D. *Corporate Financial Management*, 6th ed.; Pearson Education: Harlow, UK, 2019; Chapter 3; p. 307.
24. 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]

25. 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]
26. Gibbons, M.; Ross, S.; Shanken, J. A Test of the Efficiency of a Given Portfolio. *Econometrica* **1989**, *57*, 1121–1152. [CrossRef]
27. Cakici, N.; Fabozzi, F.; Tan, S. Size, Value, and Momentum in Emerging Market Stock Returns. *Emerg. Mark. Rev.* **2013**, *16*, 46–65. [CrossRef]
28. Affleck-Graves, J.; McDonald, B. Nonnormalities and Tests of Asset Pricing. *J. Financ.* **1989**, *44*, 889–908. [CrossRef]
29. 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.
30. Ross, S. The Arbitrage Theory of Capital Asset Pricing. *J. Econ. Theory* **1976**, *13*, 341–360. [CrossRef]
31. Benartzi, S.; Thaler, R.H. Myopic loss-aversion and the equity premium puzzle. *Q. J. Econ.* **1995**, *110*, 75–92. [CrossRef]