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Comparison Between Different Pricing Models: Evidence from the Technology Industry

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Abstract: The primary goal of this study is to investigate the applicability and analytical effectiveness of three models, namely the Capital Asset Pricing Model (CAPM), the Fama-French Three-Factor Model, and the Fama-French Five-Factor Model, within the technology industry. The study focuses on a sample of six representative technology companies, employing monthly data spanning a period of five years from 2018 to 2023. Empirical tests and regression analyses are conducted to empirically assess the performance of these three models. The results demonstrate that the Fama-French Three-Factor Model exhibits superior fitting performance compared to the CAPM model, as initially hypothesized. However, when comparing the fitting performance of the Fama-French Five-Factor Model to the Fama-French Three-Factor Model, the study reveals that the former does not exhibit a significant improvement and even shows a slight decrease in fitting effectiveness. For the technology industry, the Three-Factor Model effectively captures systematic risk and accounts for a sizable proportion of the variation in regressions. Additional factors in the Five-Factor Model might introduce additional complexity without significantly enhancing the model's explaining extent. Overall, this study underscores the importance of model selection and raises awareness about the trade-off between model complexity and explanatory capability, particularly in the technology industry.

Keywords: asset pricing models, Fama-French model, CAPM, technology industry

1. Introduction

The rise of the technology industry can be traced back to the mid-20th century, marked by breakthroughs such as the invention of the transistor and the subsequent development of integrated circuits. These milestones paved the way for the rapid proliferation of electronic devices, leading to the birth of computing giants like IBM. The late 20th century witnessed the dawn of personal computing, with companies like Apple introducing user-friendly devices that revolutionized the way individuals interacted with technology. In recent decades, the technology industry has expanded its scope beyond hardware to encompass software, telecommunications, and internet-based services. The rise of the internet and the subsequent dot-com boom ushered in a new era of digital connectivity, propelling the growth of companies like Microsoft and Adobe. Nowadays, the technology industry is characterized by unparalleled dynamism, fueled by trends such as artificial intelligence, cloud computing, and the Internet of Things. Companies like NVIDIA have leveraged advancements in graphics processing units to drive innovation in fields like gaming and artificial intelligence.

Additionally, Oracle's expertise in database technology has positioned it as a significant player in the enterprise software landscape. Plenty of academic studies have explored the intricacies of the technology industry's evolution and its multifaceted impact on the economy and society. Furthermore, research has examined the interplay between technological advancements and financial markets, particularly in terms of how technology companies' stock performances correlate with broader economic trends.

The capital asset pricing model (CAPM), formulated by Sharpe and Lintner [1, 2], significantly enhances our understanding of the risk-return relationship. Its central premise posits that expected asset returns are aligned with anticipated market portfolio returns. Variations in beta provide explanations for divergent stock returns across the spectrum. However, despite the CAPM's contributions, subsequent investigations have uncovered return patterns that it fails to explain. Consequently, scholarly exploration has gravitated towards multi-factor models for asset pricing. Fama and French extended the single-factor CAPM by incorporating two additional factors, SMB and HML, to account for size and book-to-market effects [3, 4]. This effect culminated in the Fama-French three-factor model (FF3), which has proven effective in elucidating stock return cross-sections. Building on this foundation, Fama and French introduced the Fama-French five-factor model, which supplements the three-factor model with two mimicking factors capturing return premiums associated with profitability and investment [5]. This augmentation, rooted in valuation theory and supported by contemporary empirical evidence, addresses the significant impact that profitability and investment have on asset returns. Compared to other competing asset pricing models, the five-factor model can explain more anomalies in asset pricing [6]. Importantly, Fama and French observed that FF5 outperforms its three-factor predecessor in illuminating stock return cross-sections.

However, in the technology industry, there remains a dearth of comprehensive pricing models. To address this gap and provide valuable insights for industry practitioners and financial analysts, this study is motivated to explore and identify the specific factors that should be included in pricing models within the technology industry. The intricate dynamics of this industry necessitate a nuanced understanding of factors that significantly contribute to asset pricing. The research involves a meticulous examination of the existing models, such as the CAPM, FF3, and FF5, to determine which factors align with the industry's dynamics and deserve consideration. By undertaking this exploration, the study aims to provide a clearer understanding of asset pricing in the technology industry and pave the way for more accurate valuation models.

2. Data and Method

2.1. Data Source

The study sample comprises monthly stock data of six representative companies in the technology industry, namely Apple Inc. (AAPL), Microsoft Corporation (MSFT), NVIDIA Corporation (NVDA), Adobe Inc. (ADBE), International Business Machines Corporation (IBM), and Oracle Corporation (ORCL). Due to the fact that the assessment of beta is best performed using five years' worth of monthly data [7], the sample data covers the period from January 1, 2018, to January 1, 2023. Stock data used in this analysis was obtained from Yahoo Finance [8]. Values of the factors, including $R_M - R_F$, SMB, HML, RMW, and CMA, were sourced from the website Kenneth R. French - Data Library.

2.2. Method

This study endeavors to construct linear regression equations using the stock data of the afore mentioned six technology companies, examining the regression results derived from the afore mentioned three models. Through a comparison of the Adjusted R Square and Mean Squared Error (MSE) yielded by the final fitting of these three models, the study seeks to evaluate their individual fitting effectiveness. CAPM introduces the concept of risk as measured by systematic risk, thereby offering insights into asset valuation based on its contribution to a diversified portfolio's overall risk exposure. The following equation can be used to calculate an asset's expected return:

$$R_i = R_F + \beta_i(R_M - R_F) \tag{1}$$

where $R_M - R_F$ represents the equity risk premium, which signifies the disparity between the performance of a value-weighted market index and the risk-free rate. The asset's beta gauges its systematic risk, indicating the sensitivity of its return to market portfolio fluctuations.

FF3 expands upon the CAPM by incorporating size risk and value effects factors alongside the market risk factor. This addition accommodates the recurring tendency of small-cap and value stocks to outperform markets. The following equation can be used to calculate an asset's expected return:

$$R_i = R_F + \beta_i(R_M - R_F) + \beta_s SMB + \beta_h HML \tag{2}$$

Here, SMB influences fluctuations in company market capitalization. It quantifies the disparity between the mean returns of three small-cap portfolios and three large-cap portfolios. Positive for small-cap stocks and negative for large-cap stocks, SMB acknowledges the higher required return associated with smaller companies. Capturing the disparity in book-to-market ratios, HML is the difference between the average returns on two portfolios with high and low book-to-market ratios. HML shows the value and growth bias by being positive for high book-to-market ratio companies and negative for low book-to-market ratio stocks.

FF5 extends the ability of asset pricing models to explain by integrating additional dimensions of profitability and investment, making it a valuable tool for comprehending asset behavior in diverse scenarios. The following equation can be used to calculate an asset's expected return:

$$R_i = R_F + \beta_i(R_M - R_F) + \beta_s SMB + \beta_h HML + \beta_r RMW + \beta_c CMA \tag{3}$$

The model expands on the three-factor model by incorporating two factors, enhancing its ability to explain complex asset-pricing phenomena. RMW represents profitability, and CMA denotes investment. When the proportion of production and research costs in revenue is high, profitability has a significant impact. However, in industries with a more decentralized market, profitability is relatively less taken into consideration [9].

3. Results and Discussion

3.1. Regression Results

Multiple R quantifies the correlation between predicted and actual returns, reflecting the linear relationship between the predictor variable (market return) and the response variable (stock return). With values between 0 and 1, higher numbers indicate a stronger correlation. R Square gauges the extent of explained variance in stock return by the independent variable (market return) through the pricing model. Elevated R Square values denote better model fit. Adjusted R Square considers the number of predictors in the model, curtailing overfitting and unnecessary inclusions. Standard Error measures the average deviation between observed and predicted stock returns. Lower values denote improved model fit. Mean Squared Regression (MSR), delineates the variance in stock returns explained by each model. It equals the variance difference between total and residual variance, with higher MSR signifying effective model performance. Mean Squared Error (MSE), represents the mean of squared differences between observed and predicted stock returns. Reduced MSE values indicate enhanced model accuracy.

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Table 1 displays the regression results of CAPM. The R Square values, spanning from 0.4309 to 0.5841, signify that the CAPM model represents a notable portion of the variance in the returns, ranging from 43.09% to 58.41%. The Standard Error values vary from about 0.0407 to 0.1113, suggesting that CAPM's predicted values closely align with the observed returns. The MSE values range from approximately 0.0017 to 0.0124, implying relatively accurate predictions for most stocks.

Table 1: CAPM Regression Results.

Stock	APPL	MSFT	NVDA	ADBE	IBM	ORCL
Multiple R	0.6564	0.7642	0.6371	0.7166	0.6044	0.6989
R Square	0.4309	0.5841	0.4058	0.5135	0.3653	0.4884
Adjusted R Square	0.4211	0.5769	0.3956	0.5051	0.3543	0.4796
Standard Error	0.0712	0.0407	0.1113	0.0632	0.0622	0.0542
MSR	0.2224	0.1348	0.4912	0.2444	0.1293	0.1626
MSE	0.0051	0.0017	0.0124	0.0040	0.0039	0.0029

Moving to Table 2, it showcases the FF3 regression results. R Square values, spanning from 0.5542 to 0.7805, indicate that the FF3 model explains a significant percentage of the volatility in stock returns, ranging from 55.42% to 78.05%. Values of the adjusted R Square, which range from 0.5304 to 0.7688, emphasize a reasonable fit, considering the number of predictors. Standard Error values, varying from approximately 0.0301 to 0.0966, indicate relatively low deviations between predicted and actual returns. MSE values, ranging from 0.0009 to 0.0093, further emphasize accurate predictions for most stocks.

Table 2: FF3 Regression Results.

Stock	APPL	MSFT	NVDA	ADBE	IBM	ORCL
Multiple R	0.7445	0.8835	0.7536	0.7978	0.6491	0.7363
R Square	0.5542	0.7805	0.5679	0.6364	0.4214	0.5421
Adjusted R Square	0.5304	0.7688	0.5448	0.6170	0.3904	0.5176
Standard Error	0.0641	0.0301	0.0966	0.0556	0.0605	0.0522
MSR	0.0953	0.0601	0.2291	0.1010	0.0497	0.0602
MSE	0.0041	0.0009	0.0093	0.0031	0.0037	0.0027

Table 3: FF5 Regression Results.

Stock	APPL	MSFT	NVDA	ADBE	IBM	ORCL
Multiple R	0.7492	0.8853	0.7688	0.8021	0.6853	0.7397
R Square	0.5613	0.7838	0.5911	0.6433	0.4697	0.5471
Adjusted R Square	0.5207	0.7638	0.5533	0.6103	0.4206	0.5052
Standard Error	0.0648	0.0304	0.0957	0.0561	0.0590	0.0528
MSR	0.0579	0.0362	0.1431	0.0612	0.0333	0.0364
MSE	0.0042	0.0009	0.0092	0.0031	0.0035	0.0028

Table 4: CAPM Coefficients and Significance.

		Coefficients (Beta)	Standard Error	t Stat	P-value
APPL	Intercept	0.0171	0.0092	1.8521	0.0691
	$R_M - R_F$	1.1704	0.1766	6.6271	0.0000
MSFT	Intercept	0.0147	0.0053	2.7807	0.0073
	$R_M - R_F$	0.9113	0.1010	9.0247	0.0000
NVDA	Intercept	0.0193	0.0144	1.3393	0.1857
	$R_M - R_F$	1.7394	0.2763	6.2943	0.0000
ADBE	Intercept	0.0079	0.0082	0.9600	0.3410
	$R_M - R_F$	1.2270	0.1568	7.8243	0.0000
IBM	Intercept	0.0008	0.0081	0.1048	0.9169
	$R_M - R_F$	0.8925	0.1545	5.7775	0.0000
ORCL	Intercept	0.0072	0.0070	1.0307	0.3070
	$R_M - R_F$	1.0008	0.1345	7.4418	0.0000

Table 5: FF3 Coefficients and Significance.

		Coefficients (Beta)	Standard Error	t Stat	P-value
APPL	Intercept	0.0129	0.0086	1.5067	0.1375
	$R_M - R_F$	1.1768	0.1623	7.2486	0.0000
	HML	-0.8856	0.2323	-3.8117	0.0003
	SMB	-0.7993	0.5220	-1.5312	0.1313
MSFT	Intercept	0.0105	0.0040	2.6088	0.0116
	$R_M - R_F$	0.9288	0.0762	12.1898	0.0000
	HML	-0.7213	0.1090	-6.6151	0.0000
	SMB	-0.8493	0.2450	-3.4664	0.0010
NVDA	Intercept	0.0124	0.0129	0.9581	0.3421
	$R_M - R_F$	1.7441	0.2448	7.1250	0.0000
	HML	-1.5657	0.3503	-4.4696	0.0000
	SMB	-1.3047	0.7871	-1.6577	0.1030
ADBE	Intercept	0.0042	0.0074	0.5704	0.5707
	$R_M - R_F$	1.2265	0.1408	8.7105	0.0000
	HML	-0.8597	0.2015	-4.2665	0.0001
	SMB	-0.6670	0.4528	-1.4732	0.1463
IBM	Intercept	-0.0010	0.0081	-0.1194	0.9054
	$R_M - R_F$	0.9476	0.1532	6.1853	0.0000
	HML	0.3975	0.2192	1.8132	0.0752
	SMB	-0.5821	0.4926	-1.1817	0.2423
ORCL	Intercept	0.0029	0.0070	0.4146	0.6800
	$R_M - R_F$	1.0565	0.1322	7.9944	0.0000
	HML	-0.1902	0.1891	-1.0056	0.3189
	SMB	-1.0533	0.4249	-2.4787	0.0162

Lastly, Table 3 presents the FF5 regression results. R Square values, spanning from 0.5613 to 0.7838, highlight that the FF5 model explains a large percentage of the variation in stock returns, ranging from 56.13% to 78.38%. Values of the adjusted R Square, which range from 0.5207 to 0.7638,

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underscore a satisfactory fit, considering model complexity. Standard Error values, varying from approximately 0.0304 to 0.0957, indicate relatively small deviations between predicted and observed returns. MSE values, ranging from 0.0009 to 0.0092, are quite similar to those of FF3.

Table 6: FF5 Coefficients and Significance.

		Coefficients (Beta)	Standard Error	t Stat	P-value
APPL	Intercept	0.0114	0.0089	1.2778	0.2068
	$R_M - R_F$	1.1451	0.1870	6.1238	0.0000
	HML	-0.6808	0.5450	-1.2491	0.2170
	SMB	-0.5881	0.5673	-1.0367	0.3045
	CMA	0.0928	0.8056	0.1152	0.9088
	RMW	0.7347	0.7363	0.9978	0.3228
MSFT	Intercept	0.0118	0.0042	2.8181	0.0067
	$R_M - R_F$	0.9470	0.0878	10.7850	0.0000
	HML	-0.6552	0.2559	-2.5604	0.0133
	SMB	-0.9414	0.2664	-3.5339	0.0008
	CMA	-0.0415	0.3783	-0.1096	0.9131
	RMW	-0.3101	0.3457	-0.8970	0.3737
NVDA	Intercept	0.0166	0.0131	1.2592	0.2134
	$R_M - R_F$	1.5556	0.2765	5.6271	0.0000
	HML	-0.2229	0.8058	-0.2767	0.7831
	SMB	-1.5375	0.8387	-1.8331	0.0723
	CMA	-2.0676	1.1910	-1.7360	0.0883
	RMW	0.3361	1.0885	0.3088	0.7587
ADBE	Intercept	0.0059	0.0077	0.7674	0.4462
	$R_M - R_F$	1.1666	0.1619	7.2043	0.0000
	HML	-0.3868	0.4720	-0.8194	0.4161
	SMB	-0.7605	0.4913	-1.5479	0.1275
	CMA	-0.7022	0.6976	-1.0065	0.3187
	RMW	0.0587	0.6376	0.0921	0.9270
IBM	Intercept	-0.0046	0.0081	-0.5646	0.5747
	$R_M - R_F$	1.0589	0.1703	6.2183	0.0000
	HML	-0.2632	0.4963	-0.5302	0.5981
	SMB	-0.2823	0.5166	-0.5464	0.5870
	CMA	1.4937	0.7336	2.0361	0.0467
	RMW	0.3070	0.6705	0.4578	0.6489
ORCL	Intercept	0.0028	0.0073	0.3815	0.7043
	$R_M - R_F$	1.0056	0.1526	6.5894	0.0000
	HML	0.2184	0.4448	0.4911	0.6253
	SMB	-0.9790	0.4630	-2.1146	0.0391
	CMA	-0.3092	0.6574	-0.4703	0.6400
	RMW	0.5196	0.6008	0.8647	0.3910

3.2. Coefficients and Significance

Coefficients (Beta) represent how sensitive the stock returns are to changes in the respective factors like size and value. Standard Error measures the variability or uncertainty in the estimated coefficients, giving an indication of how much the coefficient might vary from its estimated value due to random chance. The t-statistic is calculated by dividing the coefficient by its standard error, indicating whether the predictor has a significant impact on the dependent variable. The p-value assesses the statistical significance of the t-statistic. A low p-value suggests that the coefficient is statistically significant. Table 4 reveals the coefficients and significance of CAPM. P-values for $R_M - R_F$ are all close to zero, providing compelling evidence that the $R_M - R_F$ coefficient is not zero. All stocks have positive $R_M - R_F$ coefficients, indicating that they generally tend to follow the overall market trends positively. Table 5 is the coefficients and significance of FF3. The p-values for $R_M - R_F$ are close to zero, signifying the significant impact of market excess return on these stocks. The t-statistics for SMB and HML coefficients vary, indicating differing levels of significance. Table 6 refers to the coefficients and significance of FF5. Similar to previous tables, all stocks show positive $R_M - R_F$coefficients. The impact of SMB, HML, RMW, and CMA varies across stocks and models. For example, SMB is only significant for MSFT and ORCL, both of which show a negative relationship with SMB. CMA is significant for NVDA and IBM, with both showing a negative relationship with CMA. None of the stocks show a significant relationship with RMW.

3.3. Comparison and Explanation

Figure 1 and Figure 2 depict the trends of Adjusted R Square and MSE for different models, respectively. As mentioned earlier, Adjusted R Square considers the number of predictors, higher one generally indicating a better model fit. A regression model's prediction accuracy is indicated by MSE, which calculates the average squared difference between the predicted and actual values. The two figures together indicate that both FF3 and FF5 models consistently outperform the CAPM model in terms of both explanatory power (higher Adjusted R Square values) and predictive accuracy (lower MSE values) on the whole. The FF3 model, with Size and Value factors added, offers better explanatory power and predictive accuracy. The FF5 model, introducing Profitability and Investment factors, however, shows similarities with the FF3 model, implying that additional factors might not contribute significantly to improving the model's fit, especially in the technology industry.

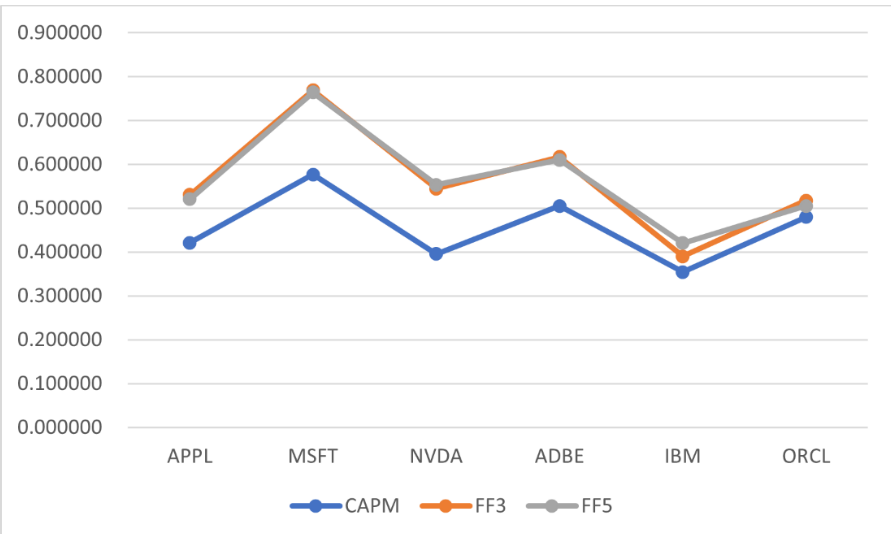

Figure 1: Adjusted R Square Trends for Different Models.

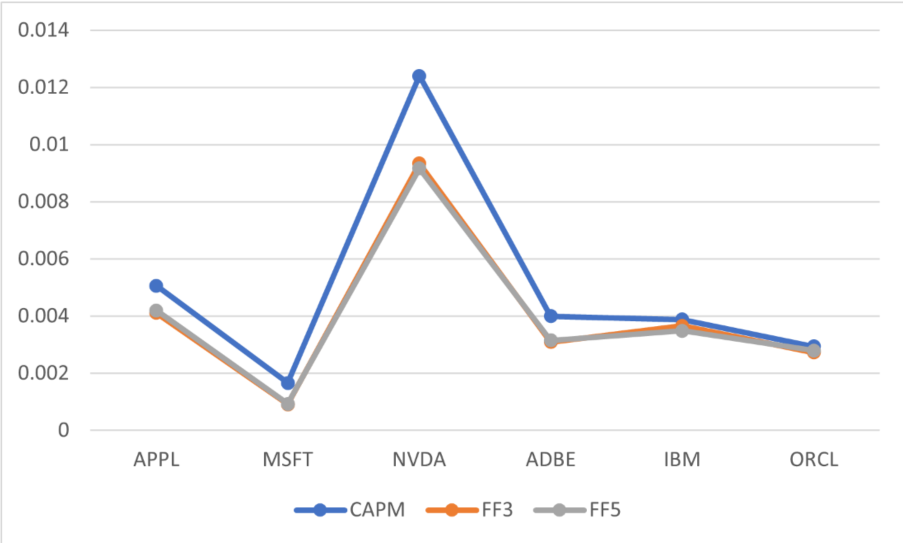

Figure 2: MSE Trends for Different Models.

4. Limitations and Future Outlooks

While the empirical results presented in this study demonstrate that fitting performance of FF5 in the technology industry is comparable to, or slightly less than, that of the three-factor model, it is important to acknowledge certain limitations and consider avenues for future research. The five-factor model's capacity to reduce pricing errors by accounting for asset-pricing anomalies is a notable finding. However, the intricacies of these anomalies and their consistent applicability across different industries remain areas of investigation. Future research could explore deeper into the specific anomalies that are better captured by the five-factor model in the technology industry and explore whether similar effects are observed in other industries.

The identification of the book-to-market (HML) factor's reduced significance when the variables representing profitability and investment are considered underscores the intricate interplay of variables within asset pricing models. This observation aligns with the stance of Hou, Xue, and Zhang, who advocate for a model considering four explanatory variables combining market and mimicking aspects representing size, profitability, and investment [10]. As the correlation between HML and CMA sheds light on the limitations of linear regression in addressing highly correlated variables, exploring non-linear models and alternative methodologies to accommodate correlated factors could yield more precise insights into their distinct contributions to explaining asset returns. Analyzing time series persistence for highly liquid instruments on the stock market for the technology industry might be a key focus for future research on prediction [11]. Additionally, it's crucial to acknowledge that the significance of factors may vary across industries and market circumstances. Subsequent research could delve into understanding the contextual determinants that lead to the redundancy of specific factors, validating these findings across diverse industries. The technology industry is known for its rapid innovation and changing market dynamics. This study's analysis is based on historical data up to 2023, and the relationships between factors and asset returns may evolve over time. Continuous monitoring and analysis of how these relationships shift in response to changes in the technology industry will be valuable for staying up-to-date with market trends.

In conclusion, while the present study provides insights into the three-factor and five-factor models' applicability in the technology industry, acknowledging the limitations of these models and their potential enhancements is vital. Future research endeavors could involve investigating the robustness of the observed trends across different industries, exploring alternative modelling

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techniques, and modeling to account for the changing nature of the technology industry. By addressing these limitations and embracing emerging methodologies, researchers can contribute to a more comprehensive understanding of asset pricing within the dynamic realm of technology.

5. Conclusion

In this study, three pricing models' effectiveness was evaluated within the technology industry. The results indicated that the FF3 model exhibited superior performance compared to the CAPM model, aligning with initial expectations. However, the FF5 model's marginal improvement and potential decrease in fitting effectiveness compared to FF3 raised questions about the necessity of additional factors. This study is not without limitations. The strong correlation between HML and CMA results in limitations in the analysis of linear regression models. The rapidly changing nature of the technology industry may also lead to evolving relationships between factors and asset returns. In conclusion, this study contributes to the understanding of asset pricing within the technology industry, highlighting the importance of model selection, especially considering the interplay between model complexity and explanatory capability. As the technology industry continues to evolve, further research could explore alternative modelling techniques and factor selection strategies.

References

[1] Sharpe, W.F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. The journal of finance, 19(3), 425-442.

[2] Lintner, J. (1975). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. In Stochastic optimization models in finance (pp. 131-155). Academic Press.

[3] Fama, E.F. and French, K.R. (1993). Common risk factors in the returns on stocks and bonds. Journal of financial economics, 33(1), 3-56.

[4] Fama, E.F. and French, K.R. (1996). Multifactor explanations of asset pricing anomalies. The journal of finance, 51(1), 55-84.

[5] Fama, E.F. and French, K.R. (2015). A five-factor asset pricing model. Journal of financial economics, 116(1), 1-22.

[6] Chiah, M., Chai, D., Zhong, A. and Li, S. (2016). A Better Model? An empirical investigation of the Fama–French five-factor model in Australia. International Review of Finance, 16(4), 595-638.

[7] Bartholdy, J. and Peare, P. (2005). Estimation of expected return: CAPM vs. Fama and French. International Review of Financial Analysis, 14(4), 407-427.

[8] Yahoo Finance. Retrieved from: https://finance.yahoo.com/ (2023). Accessed 01 Aug 2023

[9] Zhou, G. (2021, December). Analysis of the Impact of the Epidemic on the Technology-related Industry by Fama-French Five-factors Model. In 2021 3rd International Conference on Economic Management and Cultural Industry (ICEMCI 2021) (pp. 2588-2593).

[10] Barillas, F. and Shanken, J. (2018). Comparing asset pricing models. The Journal of Finance, 73(2), 715-754.

[11] Maksyshko, N. and Vasylieva, O. (2019). Diagnostics of Persistence for Quotes Dynamics in High-Tech Stock Markets. In M3E2-MLPEED (pp. 467-478).