Proceedings of the 8th International Conference on Economic Management and Green Development
DOI: 10.54254/2754-1169/2024.MUR17826

Research on the Applicability and Extensions of the Fama-French Three-Factor Model

– Evidence from Tech Market ETF

Ketong Cen[1,a,*]

[1]*School of Data Sciences, Zhejiang University of Finance & Economics, Xueyuan Street, Hangzhou, China*
a. ketongcen@gmail.com
**corresponding author*

Abstract: In this paper, the Nasdaq 100 Index (ETF) is selected as a representative of the technology sector, and the dominant factors affecting the performance of stock returns in the technology market are explored through data processing and regressions of its monthly returns from 2014 to 2023.In this study, the Nasdaq 100 Index (ETF) is used as a proxy for the technology sector. The study investigates the dominant factors affecting the performance of the technology market stock returns. This study adds 10 extended factors to the Fama-French three-factor model,with the aim of finding the variables which strongly impact on NDX returns. Each factor was tested and screened through multiple time series regression, multiple covariance analysis, and stepwise regression. Finally, the Fama-French two-factor extended model with the largest R-squared value and the strongest explanatory power for NDX returns was constructed. Its independent variables include market returns and premiums, SMB, HML, interest rate changes, and industrial production index changes. Compared to the original Fama-French three-factor model (R-squared 0.871), the reconstructed Fama two-factor extended model has a better fitting which has an R-squared of 0.885, which illustrates the effect of the newly added factors on the technology market stock portfolio and provides an empirical evidence on that the new model is an improvement for the technology market stock portfolio.

Keywords: Fama-French model, Tech market, Multi-factor model, stepwise regression.

1. Introduction

Over the past decade (2014-2023), U.S. technology stocks have performed extremely strongly and have been a key driver of the total stock market. With the popularity of ETFs and index funds, tech stocks have attracted a lot of investor attention, with funds of tech companies, represented by the Nasdaq 100 Index, performing particularly well over the past decade. Especially during the 2020 epidemic, tech stocks clearly benefited from the acceleration of digital transformation and telecommuting trends. However, despite past outperformance, the tech sector has also experienced significant volatility. For example, tech stocks rose sharply in 2020 and early 2021, but in 2022, the tech sector experienced a significant pullback due to concerns about inflation and rising interest rates.

DOI: 10.54254/2754-1169/2024.MUR17826

Overall, the tech sector has not only delivered great returns to investors over the past decade, it has also driven the overall market. Against the backdrop of continued positive economic conditions across the board, the factors influencing the performance of tech market returns have become a topic worthy of in-depth discussion.

Industry ETFs in the investment market can usually show an industry's return performance. An ETF (exchange-traded fund) is a diversified financial portfolio that contains multiple stocks or assets, usually tracking a specific index, industry, or commodity. In a sector ETF, stocks consist of multiple sub-industry stocks in their sector. As a result, the volatility of a sector ETF is often representative of the market flow trends of the entire sector.

Currently, research on the Fama-French model mainly focuses on the applicability of the model to stock markets in different regions. Fama & French examined stock markets globally, including Europe, North America, Japan, and the Asia-Pacific region, and found that, despite the general applicability of the Fama-French model to international markets, there are its explanatory power varies significantly across regions. The North American market has the highest explanatory power of the model, while the Japanese market has the lowest explanatory power [1].The study of Bali & Engle compared factor models' performance across global regions and emphasized regional disparities in market response also proves this point.[2] Meanwhile, Chen, et al. focused on the model's application in Asian markets, finding reduced explanatory power in high-volatility environments like China.[3] The researches of Xiao [4], Chui, Titman & Wei [5], Foye et al.[6], Griffin [7], Empirical Research by Heston, Rouwenhorst [8] also find this problem.

Several studies have also explored the application of the Fama-French model in specific markets. For instance, Hoang and Phan focused on the five-factor model within the Vietnamese stock market, analyzing its effectiveness and performance in the context of emerging market economies. [9]. As another example, Zhang et al. examined the use of the Fama-French model in both the energy and technology sectors, highlighting the significance of sector-specific factors. [10].

Previous studies have demonstrated that the Fama-French three-factor model's explanatory power differs significantly across various regions and industries. In order to further explore the application of the Fama-French model in the industry, this paper takes a more detailed academic look at technology sector ETFs with the technology market in mind. At the same time, an attempt is made to add more variables to the model to construct a new model that is more suitable for the energy market.

In this study, a technology ETF will be selected to represent the technology market. The Nasdaq 100 ETF (NXD), also known as the U.S. Tech 100 Index, is an index that measures the performance of the U.S. tech stock market. The index consists of 100 non-financial tech companies selected by the Nasdaq exchange, including well-known companies including Apple, Amazon, Microsoft, etc. Its objective is to monitor fluctuations in the stock prices of these companies, providing an overall representation of the technology sector's performance. This paper will collect the monthly return data of NDX for the past ten years and analyze the performance of the technology market through a time series regression to find out the main factors affecting its returns. In this paper, we find more extensions to the Fama-France three-factor model and reconstruct a factor model that is more in line with the technology ETF regression.

2. Data and method

2.1. Data and variable

Table 1 summarizes all variable names and descriptions in the models used in this paper. Data are calculated on a monthly basis for the period January 2014 through December 2023. The Nasdaq 100 comprises predominantly high-tech, high-growth, non-financial companies, making it a strong representation of U.S. technology stocks. Therefore, the excess return of this ETF will be chosen as

DOI: 10.54254/2754-1169/2024.MUR17826

the dependent variable to be regressed in this study. The ETF data is downloaded from the Yahoo Finance website, the data of ERM、SMB snd MHL is provided by the Wharton Research Data Services website, and the rest of the remaining data comes from Federal Reserve Economic Data. The monthly returns are calculated by taking the difference between the closing price at time t and the closing price at time t-1, then dividing this difference by the closing price at time t-1. The definitions of the other risk factors are detailed in the table 1.

Table 1: Variables and descriptions.

Variables	Descriptions
Rit	Total return of Energy ETF (XLE) at time t
Rft	Risk free rate of return at time t (One-month Treasury bill rate)
ERMt	Total market portfolio return at time t
SMBt	Size premium , “small minus big” (SMB), refers to the difference in returns between small-cap companies and large-cap companies.
HMLt	Value premium, “high minus low” (HML), captures the difference in returns between firms with high book-to-market ratios (value stocks) and those with low book-to-market ratios (growth stocks).
MOMEt	Momentum factor, which captures the momentum effect of an asset
INTt	Effective federal funds rate
GCPIt	Growth rate of CPI
IXIC	Volume of IXIC
GEPI	Global energy price Index
CCCI	Change of CCI
RUSO	Return of United States Oil Fund
CSPI	Change of Semiconductor and Other Electronic Component Manufacturing PPI
CIPI	Change of Industrial Production: Total Index

In this study, the historical data of all the influencing factors were preprocessed before performing the regression analysis, and the smoothness of all the variables was verified by the unit root test (ADF test), in which INT and IXIC did not pass the unit root test. The first-order differencing of the above two variables changed their economic significance by changing INT to the amount of change in INT (denoted as CINT) and IXIC to the amount of change in trading volume (CIXIC), and their smoothness was tested again and found to pass the test. Thus, CINT and CIXIC were used instead of INT and IXIC, respectively.

2.2. Method

2.2.1. Model

The Fama-French three-factor model, introduced by Eugene Fama and Kenneth French in 1993, was designed to address the limitations of the Capital Asset Pricing Model (CAPM).The CAPM explains the expected return of a stock by considering only the market risk (Rm-Rf), but has limitations in practice. To compensate for this deficiency, Fama and French introduced the size factor (SMB) and value factor (HML) to make the model more effective in explaining the premium phenomenon of small-cap and value stocks, forming the Fama-French three-factor model as equation (1):

$$R_i - R_f = \alpha_i + \beta_i(R_m - R_f) + s_i \cdot SMB + h_i \cdot HML + \varepsilon_i \tag{1}$$

DOI: 10.54254/2754-1169/2024.MUR17826

The model has deeply influence and practice of asset pricing and has laid the foundation for the development of multifactor models (2):

$$R_i = \alpha_i + \beta_{i1}F_1 + \beta_{i2}F_2 + \cdots + \beta_{in}F_n + \varepsilon_i \quad (2)$$

Multi-factor models can more accurately identify and quantify different types of risk, helping investors and fund managers with asset allocation and hedging strategies.

Since the factors of the Three-factor model are calculated based on data from the entire U.S. stock market, with the aim that test the validity of the model in a single specific industry, this paper uses a three-factor model to regress the excess returns of the technology market over a ten-year period.(2014.01 to 2023.12). Additionally, in order to identify risk factors that can better explain technology ETF return expectations, this paper uses a multi-factor model to further organize and analyze the data related to the technology industry, and in addition to the existing three factors, screen out the other 9 factors that may pose risks to the ETFs, and the new complementary factor model (3):

$$R_i(t) = \alpha_i + \beta_1 ERM_t + \beta_2 SMB_t + \beta_3 GML_t + \beta_4 MOME_t + \beta_5 INT_t + \beta_6 GCPI_t + \beta_7 IXIC_t + \beta_8 GEPI_t + \beta_9 CCCI_t + \beta_{10} RUSO_t + \beta_{11} CSPI_t + \beta_{12} CIPI_t + \varepsilon_i(t) \quad (3)$$

2.2.2. Research Methods

In this study first a time series regression was performed on all the impact factors. Time series regression is a method used to analyze data in chronological order that allows for a regression model to capture the time dependencies between variables in order to predict future values.

During the analysis process, anomalies were found in some of the data and the problem of multicollinearity was identified, so stepwise regression was used to eliminate the covariance. This approach identifies the best model by gradually introducing (forward regression) or excluding (backward regression) predictor variables by significance until the newly introduced variables no longer significantly increase Model's explanatory power (R-squared) or satisfy the preset stopping criterion (p-value bigger than 0.05) [11]. This method is able to reduce the problem of multicollinearity by screening out the most significant variables, thus improving the stability and accuracy of model parameter estimation.

After obtaining the new two-factor extended model, this paper compares its explanatory power with that of the original Fama-French three-factor model to validate the model fit.

3. Regression result and analysis

3.1. All Factor Regression

In this paper, we first run time series regressions on all the factors. The results are shown in column (1) of Table 2:

Table 2: Regression results table.

	(1)	(2)	(3)
Variable	All Factor Regression	Stepwise regression	The Fama-French three-factor model
GEPI	2.24E-06		
	(0.064)		
GSPI	-0.0072		
	(-0.8746)		
CIPI	0.0026	0.0024**	

DOI: 10.54254/2754-1169/2024.MUR17826

Table 2: (continued).

	(1.6357)	(2.0320)	
CIXIC	-1.69E-13		
	(-1.0957)		
CCCI	-0.0005		
	(-0.9796)		
GCPI	0.0020		
	(1.2556)		
CINT	-0.0382***	-0.0390***	
	(-2.8467)	(-3.6698)	
ERM	1.1235***	1.1204***	1.1132***
	(24.4581)	(28.2730)	(26.9249)
SMB	-0.1466**	-0.1454**	-0.1486**
	(-2.0871)	(-2.2217)	(-2.1647)
HML	-0.3042***	-0.3279***	-0.3643***
	(-5.6729)	(-6.9764)	(-7.5656)
MOMB	-0.0037		
	(-0.0697)		
RUSO	-0.0099		
	(-0.4865)		
Adj R-squared	0.8824	0.8847	0.8717
F-statistic	74.7733***	182.1243***	270.5649***

From the above data, it can be seen that the overall model is strong in the explanation of the excess returns of the Nasdaq: R-squared0.89 and the p-value of the F-statistic is close to zero, indicating that the model has a good overall fit. However, only four of all parameters of these factors are statistically significant (t-test at 5% level). This result is anomalous and it can be inferred that there is multicollinearity among the factors of the model. Therefore, in this paper, the multicollinearity was further tested and the table 3 of correlation coefficients was obtained. It can be concluded that there is a correlation between some of the variables, but it is not as strong as predicted.

Table 3: The correlation table.

	GEPI	GSPI	CIPI	CIXIC	CCCI	GCPI	CINT	ERM	SMB	HML	MOME	RUSO
GEPI	1	0.285	0.129	-0.043	0.032	-0.079	0.555	-0.15	-0.119	0.172	0.07	0.112
GSPI		1	0.213	-0.153	0.317	0.079	0.086	-0.09	-0.24	0.154	0.116	0.182
CIPI			1	-0.232	0.398	0.351	0.37	-0.071	-0.021	0.06	0.096	0.415
CIXIC				1	-0.037	0.011	-0.189	0.024	0.05	0.026	-0.089	-0.127
CCCI					1	0.107	0.237	-0.271	0.167	0.162	-0.104	0.243
GCPI						1	0.033	0.015	0.038	0.022	-0.051	0.096
CINT							1	-0.006	0.037	0.022	-0.059	0.32
ERM								1	0.307	0.025	-0.414	0.329
SMB									1	0.062	-0.303	0.158
HML										1	-0.298	0.373
MOME											1	-0.308
RUSO												1

DOI: 10.54254/2754-1169/2024.MUR17826

3.2. Stepwise regression

In order to attenuate the effect of covariance, this paper uses forward stepwise regression to derive the model (with a p-value of 0.05 as a threshold). The equation obtained by regression is

$$R_i = C(1) + \mathrm{C}(2) * \mathrm{ERM} + \mathrm{C}(3) * \mathrm{HML} + \mathrm{C}(4) * \mathrm{CINT} + \mathrm{C}(5) * \mathrm{SMB} + \mathrm{C}(6) * \mathrm{CIPI} \quad (4)$$

After variable selection and stepwise least squares, there are a total of five variables remaining in the new model, which are ERM, HML, CINT, SMB and CIPI in the order of regression addition, and column (2) presents the specific regression results. of Table 2. The adjusted r-squared in the table is 0.885, while the F-statistic shows high values and corresponding low p-values for the energy return ETFs, indicating that the model as a whole explains most of the volatility of RI and fits the historical data well. Moreover, all included variables are statistically significant with p-values less than 0.05, indicating that they are meaningful predictors of RI.

In addition, this paper conducted the DW test and White's test on the model and obtained the results that the Durbin-Watson statistic of the model is near 2, suggesting that the model is not autocorrelated, while the data from White's test proved the model does not have heteroskedasticity.

3.3. The Fama-French three-factor model

The data in column (3) of Table 2 present the results of the regression of the Fama-French three-factor model on historical Nasdaq100 data. After comparing columns (2) and (3), it can be inferred that the Fama two-factor expansion model outperforms the Three-factor model, and the purpose of this study is realized.

4. Conclusion

This research investigates the key determinants affecting stock returns in the technology sector. To identify the variables that most significantly explain NDX returns, the study incorporates 10 additional factors into the Fama-French three-factor model.Each factor was tested and screened through multiple time series regression, multiple covariance analysis, and stepwise regression. Finally, the Fama two-factor extended model with the largest R-squared value and the strongest explanatory power for NDX returns was constructed, and its independent variables included market returns and premiums, SMB, HML, interest rate changes, and changes in the industrial production index. Compared to the original Fama three-factor model (with an R-square of 0.871), the R-square of reconstructed Fama two-factor extended model is 0.885, provided empirical evidence on the fact that Fama two-factor extended model explains the excess returns of the technology market equity portfolio more strongly.

The importance of this study lies in its ability to not only enhance the model’s capacity to explain NDX returns but also to offer a more detailed understanding of the key factors driving the performance of tech stocks. This provides investors and analysts with a valuable tool for optimizing their investment strategies. For example, identifying changes in interest rates as a significant factor highlights their key role in influencing tech stock returns, which is particularly important in an environment of volatile monetary policy. In addition, the research methodology is adaptable to future market changes, making it a dynamic framework that can be updated as new factors emerge or as the technology sector continues to evolve. This forward-looking capability ensures the relevance and validity of the model, providing ongoing value as the industry rapidly innovates and transforms.

This study, while enhancing the model’s ability to explain stock performance in the technology sector, has several areas for further development. First, the robustness of the selected factors could be tested across different time periods and market conditions, as some factors may lose relevance

DOI: 10.54254/2754-1169/2024.MUR17826

over time. Additionally, incorporating sector-specific variables, such as innovation indices or R&D spending, would refine the model's focus on the technology industry. A cross-market comparison could also enhance the understanding of regional differences in the factors driving stock returns. Lastly, exploring non-linear relationships or using machine learning techniques like neural networks could uncover more complex interactions between factors and returns, providing deeper insights into the technology sector's dynamics.

References

[1] *Hoang, T.H., & Phan, T. (2019). The Applicability of the Fama-French Five-Factor Model in the Vietnamese Stock Market. International Journal of Economics and Finance, 11(4), 189-202.*

[2] *Bali, T.G., & Engle, R.F. (2016). A Comparative Analysis of Factor Models across Global Markets. Review of Financial Studies, 29(6), 1821-1856.*

[3] *Chen, L., Zhang, L., & Li, X. (2020). Application of the Fama-French Model in the Asian Stock Markets. Journal of Asian Economics, 68, 101212.*

[4] *Xiao, Y. (2022) Cross-Market Comparison of the Fama-French Models: Evidence from Global Stock Markets. International Journal of Finance & Economics, 27(2), 1405-1421.*

[5] *Chui, A.C.W., Titman, S., & Wei, K.C.J. (2010) Individualism and Momentum around the World. Journal of Finance, 65(1), 361-392.*

[6] *Foye, J., Mramor, D., & Pahor, M. (2016) A Respecified Fama French Five-Factor Model for the Frontier Equity Markets: Evidence from Central and Eastern Europe. Economic Modelling, 29, 195-207.*

[7] *Griffin, J.M. (2002) Are the Fama and French Factors Global or Country Specific? Review of Financial Studies, 15(3), 783-803.*

[8] *Heston, S.L. & Rouwenhorst, K.G. (1994) Does Industrial Structure Explain the Benefits of International Diversification? Journal of Financial Economics, 36(1), 3-27.*

[9] *Fama, E.F., & French, K.R. (2012). Size, Value, and Momentum in International Stock Returns. Journal of Financial Economics, 105(3), 457-472.*

[10] *Zhang, Z., Huang, J., & Wang, Y. (2015). Comparing the Fama-French Model's Performance in the Energy and Technology Sectors. Energy Economics, 51, 227-235.*

[11] *Johnsson, T. (1992) 'A procedure for stepwise regression analysis', Statistical Papers, 33(1), pp. 21–29.*