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An Empirical Analysis on Performance of the Fama and French Five-Factor Model in Different Industries

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Abstract. This study examines the performance of the Fama and French five-factor model (FF5) in various industries. The analysis encompasses a comprehensive period from January 1990 to February 2023, encompassing 17 distinct industry portfolios. By comparing FF5 against other prominent asset pricing models such as the Capital Asset Pricing Model (CAPM), Fama-French three-factor model (FF3), Carhart four-factor model (CFFM), and Fama-French six-factor model (FF6), the research aims to identify the most effective factor models for each industry. The results indicate that FF5 consistently outperforms other models across the majority of industries studied. This suggests that FF5 provides a robust framework for understanding and evaluating asset pricing in diverse industry settings. The findings contribute to the growing body of literature on asset pricing models, supporting the application of FF5 as an effective tool for assessing risk and expected returns across different industries. The study's methodology involves constructing industry portfolios based on firms operating within specific sectors and examining the performance of various factor models within each portfolio. The analysis utilizes a range of statistical techniques, including regression analysis, to assess the performance and significance of the different factors within each model. The findings hold significant implications for portfolio managers, investors, and financial analysts, as they highlight the importance of considering multiple factors beyond the traditional CAPM when evaluating investment opportunities in different industry sectors.

Keywords: Asset Pricing Models, Different Industries, COVID-19 Pandemic.

1 Introduction

Asset pricing models are crucial tools for companies to determine the value of their assets while considering factors such as risk, expected returns, and market conditions. Over the years, several models have been proposed, including the CAPM, FF3, CFFM, FF5 and FF6 [1-4]. FF5 has received considerable attention due to its ability to explain stock returns based on market risk, size, value, profitability, and investment. While Sehgal and Balakrishnan discovered that the FF5 model outperformed the CAPM in explaining outcomes for the majority of portfolios built based on business characteristics, there are concerns about the model's ability to produce consistent

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and accurate results across different industries [5]. Therefore, it is crucial to evaluate the model's robustness across industries to determine if it can provide reliable insights into various sectors of the economy. This paper's goal is to assess FF5's performance across several sectors using data from NYSE, ASE and the Nasdaq Stock. By analysing sector-level data, the study aims to determine the extent to which FF5 can explain changes in stock returns across sectors. This research is significant because the applicability and accuracy of the FF models may vary across industries, depending on specific characteristics such as their level of competition, technological advancement, and regulatory environment, among others. Understanding the robustness of the model across different industries is, therefore, critical to assessing its validity and applicability in a broad range of financial and economic decision-making contexts.

Previous studies have provided mixed results on the performance of FF5 in different industries. With FF5, which expands upon the initial three-factor model by including profitability and investment elements, has been widely used to explain asset returns in various industries. However, there is still debate about the robustness of the model across different industries. The US market's cross-section of stock returns for portfolios organized by size, book-to-market, and profitability are found to be well explained by FF5. It also reports that the model works similarly well in international markets. Lewellen, Nagel, and Shanken, however, contend that FF5 falls short of explaining the cross-section of stock returns in a number of sectors, such as utilities, transportation, and telecommunications [6]. They find that the model's profitability factor is largely redundant and the investment factor is weak in explaining returns. They propose that the cross-section of stock returns may require the explanation of industry-specific factors. Other research have found FF5 to be helpful in explaining the cross-section of stock returns in 17 established economies, but less so in emerging markets, with mixed results. However, they do not test the model's performance in different industries. Additionally, Sarwar, Mateus, and Todorovic looked into the risk-adjusted performance of US sector portfolios using FF5 [7]. They discovered that the five-factor model, as opposed to the FF3 model, better predicted the returns of US sector portfolios, but all sectors still saw significant alphas from time to time. However, by comparing the FF models to not only the three-factor and five-factor models but also the CFFM and FF6, our study attempts to further explore the resilience of the FF models in various industries. By expanding the scope of the study to include more factors, we hope to provide a more comprehensive analysis of the FF models' effectiveness in different industries.

The rest of this essay is organized as follows: The data and methodology utilized in the analysis are given in Section 2. Results and a robustness analysis are presented in Section 3 before Section 4 offers a conclusion. Overall, this work adds to the body of knowledge on asset pricing models and sheds light on how they might be used to various industries.

2 Methodology

2.1 Data Collection and Portfolio Construction

In this study, the dataset used is sourced from the CRSP (Center for Research in Security Prices) database. It encompasses monthly returns for 17 industry portfolios. These portfolios are constructed based on the four-digit Standard Industrial Classification (SIC) code assigned to each stock at the end of June of year t. The sample includes stocks from the NYSE, AMEX, and NASDAQ exchanges.

To determine the SIC codes, Compustat SIC codes are utilized for the fiscal year ending in the calendar year t-1. However, if Compustat SIC codes are unavailable, the CRSP SIC codes for June of year t are used as a substitute. The study period spans from January 1990 to February 2023, providing a comprehensive dataset for analysis and examination of long-term trends and patterns. The monthly returns for each industry portfolio are computed from July of year t to June of year t+1.

The dataset includes the following industry portfolios: Food, Mines, Oil, Clths, Durbl, Chems, Cnsum, Cnstr, Steel, FabPr, Machn, Cars, Trans, Utils, Rtail, Finan, and Other. Both value-weighted and equal-weighted returns are provided for each portfolio, allowing for different approaches to measuring portfolio performance and assessing the impact of stock weighting methodologies. This dataset offers a rich source of information for conducting research and analysis on industry-specific returns, exploring market trends, and evaluating investment strategies over a significant period of time.

2.2 Modelling

Our study aims to identify the best factor models for each industry by comparing five different models. These models include the CAPM, which uses only market premium factors to explain asset prices; FF3, which adds size and value premiums as pricing factors; CFFM, which includes momentum; FF5, which adds to the FF3 model which adds profitability and investment premium factors; and FF6, which includes momentum factors in addition to those used in the FF5 model. The details of FF6 are as follows:

$$r_{i,t} - r_{f,t} = a_i + \beta_{i,MKT}MKT_t + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,RMW}RMW_t + \beta_{i,CMA}CMA_t + \beta_{i,MOM}MOM_t + \varepsilon_{i,t} \tag{1}$$

Where

$r_{i,t} - r_{f,t}$ =The return in excess of the risk-free interest rate at time t;

MKT_t =The expected excess return of the market;

SMB_t =The performance difference between small-cap and large-cap stocks;

HML_t =The difference in returns between high book-to-market ratio (value) stocks and low book-to-market ratio (growth) stocks;

RMW_t =The difference between companies with strong profitability and those with weak profitability;

CMA_t =The performance difference between companies with conservative investment strategies and those with aggressive investment strategies;

MOM_t =The difference in average return between a portfolio consisting of stocks with high prior returns and a portfolio consisting of stocks with low prior returns.

3 Empirical Results

3.1 Descriptive Statistics

The study analyzed the performance of 17 industry portfolios using the Fama-French five-factor model, consisting of market (MKT), size (SMB), value (HML), momentum (MOM), and profitability (RMW and CMA) factors. Based on the summary statistics in Table 1, all factors exhibit positive mean returns, suggesting a positive association with portfolio performance. The momentum factor exhibits the highest average return of 0.62%, followed by the market factor at 0.55%, implying that portfolios exposed to these factors may generate higher returns than those that are not exposed to them.

Furthermore, all factors exhibit statistical significance with t-statistics greater than 2, which indicates that their impact on portfolio returns is statistically significant at a 95% confidence level. Hence, the positive relationship between each factor and portfolio returns is unlikely to be attributed to chance. Additionally, the t-statistic value provides insight into the relative importance of each factor, and in this study, the market and momentum factors exhibit the highest t-statistics, indicating their greater influence on explaining portfolio returns than the other factors.

Table 2 presents the correlation matrix of the asset pricing factors, revealing the interrelationships between these factors. Overall, there is moderate correlation between the FF factors, but little correlation with the momentum factor. Specifically, the matrix highlights a moderate correlation between the different Fama French factors, with the highest correlation observed between HML and RMW (0.684). SMB exhibited negative correlations with HML (-0.029) and RMW (-0.101), while it had positive correlations with MKT (0.281) and CMA (-0.068). MOM had weak correlations with the other factors, with the only notable correlation being a negative association with SMB (-0.350).

The negative correlation between RMW and MKT (-0.367) indicates that profitable companies tend to outperform the market when the overall market performance is weak. Furthermore, the negative correlation between HML and CMA (-0.193) suggests that companies with high book-to-market ratios tend to invest less, while the positive correlation between HML and RMW (0.684) implies that these companies tend to be profitable and invest aggressively. It is important to recognize that the estimation of the correlation matrix is contingent on the sample period, and thus these correlations may differ based on the sample selection.

Table 1. Summary Statistics.

variable	mean	sd	p25	p50	p75	min	max	t-statistics
MKT	0.55%	4.50%	-0.20%	0.92%	3.43%	-23.24%	16.10%	3.292
SMB	0.23%	3.02%	-1.51%	0.10%	2.03%	-15.35%	18.34%	2.033
HML	0.30%	2.97%	-1.38%	0.25%	1.75%	-13.95%	12.75%	2.735
MOM	0.62%	4.23%	-0.97%	0.74%	2.91%	-34.30%	18.20%	3.899
RMW	0.28%	2.22%	-0.79%	0.02%	1.31%	-18.73%	13.09%	3.353
CMA	0.29%	2.06%	-1.00%	0.10%	1.52%	-6.92%	9.05%	3.781

Table 2. Correlation matrix.

	MKT	SMB	HML	MOM	RMW
MKT	1				
SMB	0.281	1			
HML	-0.211	-0.029	1		
MOM	-0.182	-0.350	0.093	1	
RMW	-0.367	-0.101	0.684	-0.015	1

3.2 Regression Results: All Industries in the Portfolio

The key factors affecting returns across industries are examined in this part, and the effectiveness of various asset pricing methods is contrasted. Tables 3, 4 & 5 represent the results for 17 industry portfolios over the entire sample period from January 1990 to February 2023. Comparing the results of the CAPM and FF3, it finds that the inclusion of SMB and HML in the latter results in a significant improvement in the adjusted R2. This suggests that the addition of these two factors can better explain the variability of stock returns. The analysis indicates that the FF factor is important in describing the average returns of the 17 industries over the sample period.

CFFM is often augmented with a momentum factor to produce the five-factor model of Fama and French. It finds that 11 industries have a statistically significant and negative coefficient on momentum (MOM). This suggests that in these 11 sectors, stocks that have recently performed well (i.e. high momentum stocks) may actually underperform in the future. For most of the 17 sectors, however, the coefficient on MOM is statistically significant at the 1% level, indicating a strong relationship between momentum and future stock performance. Nonetheless, there are some MOM coefficients that are not statistically significant at the 10% level and may be unreliable or not robust. This analysis also tests the applicability of FF5 to the Chinese stock market. By adding RMW and CMA to FF3, FF5 aims to capture the characteristics of average returns associated with size, B/M, profitability, and investment. It is found that the adjusted R^2 of FF3 improves slightly with the inclusion of RMW and CMA. FF5 performs better in terms of adj-R^2 than CFFM. The coefficients of RMW and CMA show statistically significant relationships with stock returns, and these relationships are robust even with the addition of the momentum factor. The fact that HML remains significant after the inclusion of these two new factors suggests that the value factor is not redundant.

Table 3. Comparison of models (CAPM, FF3 and CFFM) performance using 17 industry portfolios.

Var.	CAPM	FF3			Carhart4			
	MKT	MKT	SMB	HML	MKT	SMB	HML	MOM
Food	0.7053***	0.7558***	-0.1675***	0.1361***	0.7641***	-0.1667***	0.1500***	0.0409*
	(0.0317)	(0.0320)	(0.0505)	(0.0507)	(0.0325)	(0.0513)	(0.0493)	(0.0386)
Mines	1.0171***	0.9654***	0.3932***	0.1613***	0.9714***	0.3938***	0.1714***	0.0409
	(0.0567)	(0.0609)	(0.0836)	(0.0804)	(0.0600)	(0.0842)	(0.0804)	(0.0598)
Oil	0.8698***	0.9595***	-0.1061***	0.5001***	0.9755***	-0.1045***	0.5269***	0.0787*
	(0.0524)	(0.0529)	(0.0685)	(0.0933)	(0.0531)	(0.0684)	(0.0909)	(0.0529)
Clths	1.1003***	1.0644***	0.3902***	0.2708***	1.0297***	0.3867***	0.2126***	-0.1710***
	(0.0414)	(0.0412)	(0.0947)	(0.0740)	(0.0400)	(0.0881)	(0.0658)	(0.0432)
Durbl	1.0855***	1.0693***	0.1829***	0.1318***	1.0451***	0.1805***	0.0912***	-0.1192***
	(0.0324)	(0.0321)	(0.0503)	(0.0545)	(0.0298)	(0.0466)	(0.0532)	(0.0480)
Chems	1.0609***	1.1157***	-0.0288***	0.3542***	1.0961***	-0.0308***	0.3215***	-0.1192*
	(0.0325)	(0.0317)	(0.0459)	(0.0508)	(0.0321)	(0.0437)	(0.0514)	(0.0407)
Cnsum	0.7233***	0.7738***	-0.3478***	-0.1077***	0.7847***	-0.3468***	-0.0895***	0.0533
	(0.0358)	(0.0328)	(0.0549)	(0.0567)	(0.0335)	(0.0555)	(0.0576)	（0.0444）
Cnstr	1.1684***	1.1523***	0.2521***	0.2188***	1.154***	0.2522***	0.2215***	0.0533***
	(0.0298)	(0.0286)	(0.0481)	(0.0483)	(0.0278)	(0.0484)	(0.0474)	(0.0355)
Steel	1.3328***	1.3084***	0.4081***	0.3781***	1.2775***	0.4051***	0.3263***	-0.1523***
	(0.0473)	(0.0446)	(0.0627)	(0.0760)	(0.0441)	(0.0630)	(0.0766)	(0.0532)
Fab Pr	1.0136***	0.9944***	0.2436***	0.1923***	0.9791***	0.2421***	0.1666***	-0.0753**
	(0.029)	(0.0299)	(0.0708)	(0.0530)	(0.0290)	(0.0683)	(0.0487)	(0.0407)
Machn	1.2480***	1.1627***	0.1874***	-0.3577***	1.1409***	0.1853***	-0.3942***	-0.1074***
	(0.0311)	(0.0311)	(0.0512)	(0.0521)	(0.0291)	(0.0533)	(0.0549)	(0.0394)

Cars	1.1487***	1.1694***	0.1320***	0.3268***	1.1184***	0.1270***	0.2415***	-0.2507
	(0.0547)	(0.0547)	(0.0786)	(0.0800)	(0.0518)	(0.0717)	(0.0754)	(0.0577)
Trans	1.0851***	1.0899***	0.1969***	0.3018***	1.0816***	0.1961***	0.2878***	-0.0411**
	(0.0307)	(0.0287)	(0.0539)	(0.0501)	(0.0291)	(0.0528)	(0.0471)	(0.0348)
Utils	0.5234***	0.6086***	-0.2052***	0.3334***	0.6218***	-0.2038***	0.3555***	0.0652***
	(0.035)	(0.0333)	(0.0471)	(0.0529)	(0.0336)	(0.0476)	(0.0545)	(0.0372)
Rtail	0.9794***	0.9628***	0.0396***	-0.0645***	0.9443***	0.0378***	-0.0956***	-0.0912***
	(0.0335)	(0.0360)	(0.0641)	(0.0610)	(0.0359)	(0.0609)	(0.0574)	(0.0371)
Fi-nan	1.0712***	1.1517***	-0.0506***	0.5088***	1.1348***	-0.0523***	0.4806***	-0.0828***
	(0.0264)	(0.0245)	(0.0403)	(0.0378)	(0.0245)	(0.0382)	(0.0379)	(0.0258)
Other	1.0327***	1.0014***	0.0511***	-0.1546***	0.9959***	0.0505***	-0.1639***	-0.0273
	(0.0124)	(0.0122)	(0.0197)	(0.0205)	(0.0129)	(0.0195)	(0.0211)	(0.0176)
Obs.	716		716			716		
R2	0.6257		0.6608			0.6661		

Note: Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4. Comparison of models (FF5) performance using 17 industry portfolios.

Var.	FF5				
	MKT	SMB	HML	RMW	MKT
Food	0.8188***	-0.0263***	-0.0676***	0.5662***	0.3979***
	(0.0291)	(0.0451)	(0.0549)	(0.0566)	(0.0733)
Mines	1.0052***	0.3942***	-0.0084***	-0.0165***	0.3873***
	(0.0615)	(0.0861)	(0.1133)	(0.1334)	(0.1727)
Oil	1.0018***	-0.0677***	0.3374***	0.1412***	0.3531***
	(0.0534)	(0.0715)	(0.1345)	(0.0937)	(0.1589)
Clths	1.0865***	0.5391***	0.2455***	0.6203***	-0.0134***
	(0.0378)	(0.0635)	(0.0829)	(0.0933)	(0.1102)
Durbl	1.0861***	0.2746***	0.1026***	0.3803***	0.0229***
	(0.0319)	(0.0443)	(0.0609)	(0.0665)	(0.0902)
Chems	1.151***	0.0433***	0.2368***	0.2878***	0.2337***
	(0.0305)	(0.0431)	(0.0649)	(0.0604)	(0.0879)
Cnsum	0.8383***	-0.2292***	-0.3284***	0.4699***	0.4473***
	(0.0310)	(0.0485)	(0.0622)	(0.0699)	(0.0913)
Cnstr	1.1723***	0.3301***	0.1697***	0.3207***	0.0750***
	(0.0278)	(0.0401)	(0.0582)	(0.0628)	(0.0877)
Steel	1.3094***	0.3237***	0.3350***	-0.3585***	0.1387***
	(0.0464)	(0.0664)	(0.0938)	(0.1049)	(0.1408)
FabPr	1.014***	0.3309***	0.1487***	0.3601***	0.0578***
	(0.0278)	(0.0491)	(0.0605)	(0.0805)	(0.0814)

Machn	1.1247***	0.1074***	-0.2322***	-0.3196***	-0.2483***
	(0.0294)	(0.0467)	(0.0581)	(0.0846)	(0.0976)
Cars	1.1789***	0.1656***	0.3015***	0.1372***	0.0418***
	(0.0601)	(0.0737)	(0.1061)	(0.1164)	(0.1652)
Trans	1.1071***	0.3075***	0.2798***	0.4601***	-0.0023***
	(0.0276)	(0.0411)	(0.0482)	(0.0617)	(0.0754)
Utils	0.6486***	-0.1680***	0.1794***	0.1366***	0.3338***
	(0.0331)	(0.0481)	(0.0712)	(0.0682)	(0.1027)
Rtail	0.9792***	0.1446***	-0.0856***	0.4369***	-0.0019***
	(0.0330)	(0.0503)	(0.0763)	(0.0652)	(0.0966)
Finan	1.1249***	-0.0499***	0.6237***	0.0169***	-0.2627***
	(0.0245)	(0.0382)	(0.0501)	(0.0476)	(0.0666)
Other	0.9887***	0.0067***	-0.1206***	-0.1819***	-0.0564***
	(0.0122)	(0.0204)	(0.0225)	(0.0287)	(0.0369)
Obs.			716		
R2			0.6784		

Note: Standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 5. Comparison of models (FF6) performance using 17 industry portfolios.

Var.	FF6					
	MKT	SMB	HML	RMW	CMA	MOM
Food	0.8194***	-0.0265***	-0.0654***	0.5652***	0.3963***	0.0042***
	(0.0297)	(0.0453)	(0.0513)	(0.0579)	(0.0730)	(0.0353)
Mines	1.0076***	0.3938***	-0.0008***	-0.0193***	0.3818***	0.0148***
	(0.0607)	(0.0859)	(0.1128)	(0.1345)	(0.1727)	(0.0608)
Oil	1.0113***	-0.0695***	0.3687***	0.1297***	0.3304***	0.0607***
	(0.0536)	(0.0716)	(0.1331)	(0.0925)	(0.1591)	(0.0527)
Clths	1.0554***	0.5451***	0.1439***	0.6579***	0.0602***	-0.1976***
	(0.0378)	(0.0582)	(0.0769)	(0.0821)	(0.1047)	(0.0346)
Durbl	1.0645***	0.2788***	0.0321***	0.4063***	0.0740***	-0.1371***
	(0.0299)	(0.0436)	(0.0602)	(0.0645)	(0.0874)	(0.0433)
Chems	1.1323***	0.0469***	0.1757***	0.3104***	0.2779***	-0.1187***
	(0.0310)	(0.0423)	(0.0640)	(0.0579)	(0.0870)	(0.0371)
Cnsum	0.8412***	-0.2297***	-0.3188***	0.4664***	0.4404***	0.0185***
	(0.0316)	(0.0485)	(0.0617)	(0.0721)	(0.0907)	(0.0404)
Cnstr	1.1712***	0.3303***	0.1661***	0.3220***	0.0776***	-0.0070***
	(0.0276)	(0.0400)	(0.0574)	(0.0638)	(0.0884)	(0.0328)
Steel	1.2862***	0.3282***	0.2590***	-0.3304***	0.1938***	-0.1478***
	(0.0460)	(0.0651)	(0.0921)	(0.1035)	(0.1374)	(0.0514)
FabPr	0.9994***	0.3337***	0.1009***	0.3778***	0.0925***	-0.0929***
	(0.0279)	(0.0478)	(0.0565)	(0.0795)	(0.0802)	(0.0346)
Machn	1.1109***	0.1101***	-0.2773***	-0.3029***	-0.2156***	-0.0876***
	(0.0286)	(0.0463)	(0.0611)	(0.0832)	(0.0947)	(0.0352)
Cars	1.1376***	0.1735***	0.1661***	0.1872***	0.1399***	-0.2632***
	(0.0576)	(0.0703)	(0.1027)	(0.1095)	(0.1616)	(0.0558)
Trans	1.0978***	0.3093***	0.2493***	0.4714***	0.0197***	-0.0593***
	(0.0280)	(0.0408)	(0.0484)	(0.0613)	(0.0767)	(0.0293)
Utils	0.6561***	-0.1695***	0.204***	0.1276***	0.3160***	0.0478***
	(0.0337)	(0.0484)	(0.0730)	(0.0680)	(0.1026)	(0.0354)
Rtail	0.9619***	0.148***	-0.1420***	0.4577***	0.0389***	-0.1096***
	(0.0336)	(0.0491)	(0.0726)	(0.0615)	(0.0935)	(0.0354)
Finan	1.1132***	-0.0476***	0.5853***	0.0311***	-0.2349***	-0.0745***
	(0.0244)	(0.0374)	(0.0506)	(0.0462)	(0.0663)	(0.0251)
Other	0.9857***	0.0072***	-0.1303***	-0.1783***	-0.0494***	-0.0188***
	(0.0125)	(0.0201)	(0.0230)	(0.0285)	(0.0368)	(0.0166)
Obs.				716		
R2				0.6784		

Note: Standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 6. Comparison of Model Performance.

CAPM						FF3					
variable	mean	sd	median	min	max	variable	mean	sd	median	min	max
a_i	0	0.1505	0.0029	-0.3069	0.2767	a_i	0.0101	0.1215	0.0345	-0.2074	0.2038
A$\|a_i\|$	0.1	0.1022	0.0644	0.0015	0.3069	A$\|a_i\|$	0.1008	0.0638	0.0919	0.0137	0.2074
s.e.	0.1	0.0329	0.1123	0.0794	0.2036	s.e.	0.1116	0.03	0.1033	0.0646	0.1824
t-value	0.2	1.2182	0.0296	-2.2397	2.3662	t-value	0.0422	1.0964	0.3304	-1.9646	1.6727
p-value	0.5	0.3476	0.5129	0.0179	0.9872	p-value	0.4142	0.2723	0.3359	0.0494	0.9296
FF4						FF5					
variable	mean	sd	median	min	max	variable	mean	sd	median	min	max
a_i	0	0.1084	0.0021	-0.1799	0.2078	a_i	0.0035	0.0934	0.0215	-0.2419	0.1205
A$\|a_i\|$	0.1	0.0637	0.0858	0.0011	0.2078	A$\|a_i\|$	0.0673	0.0626	0.0462	0.0023	0.2419
s.e.	0.1	0.0208	0.1059	0.0667	0.1392	s.e.	0.0914	0.0228	0.0934	0.0613	0.1498
t-value	0	1.0225	0.0198	-1.7101	1.6434	t-value	0.063	1.0062	0.2102	-2.5642	1.2543
p-value	0.5	0.3244	0.4088	0.0872	0.9916	p-value	0.5402	0.3096	0.603	0.0103	0.9797

FF6					
variable	mean	sd	median	min	max
a_i	0.0025	0.0864	0.0284	-0.2275	0.1131
A$\|a_i\|$	0.0661	0.0532	0.0427	0.0004	0.2275
s.e.	0.0874	0.0159	0.0883	0.0618	0.1152
t-value	0.0675	0.9411	0.3381	-2.3163	1.1983
p-value	0.5154	0.2651	0.5436	0.0205	0.9948

Note: Standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 7. FF6 performance during COVID-19.

Var.	FF6					
	MKT	SMB	HML	RMW	CMA	MOM
Food	0.6003***	0.0310*	0.1035***	0.4351***	0.2808***	0.0615*
	(0.1036)	(0.2567)	(0.1256)	(0.2844)	(0.2096)	(0.1246)
Mines	1.0144***	0.0906***	0.0845***	-0.0013***	0.5390***	-0.2489*
	(0.1706)	(0.3731)	(0.2843)	(0.3967)	(0.4515)	(0.2837)
Oil	1.3857***	0.0691*	1.3458***	-1.1411***	0.5084***	-0.2393***
	(0.2398)	(0.4587)	(0.3163)	(0.4213)	(0.4282)	(0.3049)
Clths	1.0966***	0.3864***	-0.2504***	0.6344***	0.0059***	-0.0319*
	(0.1491)	(0.2594)	(0.1980)	(0.3001)	(0.3530)	(0.1592)
Durbl	1.1418***	0.6467***	-0.2636***	-0.0100***	0.0954***	0.0285***
	(0.1398)	(0.2377)	(0.1535)	(0.2954)	(0.2713)	(0.1690)*
Chems	1.0764***	0.1727***	0.2149***	0.1401***	0.3661***	-0.1260**
	(0.0978)	(0.2219)	(0.1397)	(0.2242)	(0.1980)	(0.1584)
Cnsum	0.5475***	0.0314*	-0.2864***	0.4899***	0.7089***	0.0792*
	(0.0812)	(0.1654)	(0.1116)	(0.2269)	(0.1776)	(0.0822)
Cnstr	0.9730***	0.3875***	0.1415***	1.0401***	-0.4651***	0.3086*
	(0.1380)	(0.3162)	(0.1644)	(0.3170)	(0.2622)	(0.1966)**
Steel	1.2477***	0.2737***	0.3388***	0.2196***	0.3420***	-0.6378***
	(0.2254)	(0.6993)	(0.3961)	(0.6042)	(0.5424)	(0.3320)
FabPr	0.8719***	0.2383***	0.1093***	0.1953***	-0.3290***	-0.1566**
	(0.0903)	(0.1843)	(0.1199)	(0.1931)	(0.1667)	(0.1160)
Machn	1.0513***	0.2718***	-0.2072***	0.3296***	0.1216***	-0.0130**
	(0.1064)	(0.2232)	(0.1361)	(0.3032)	(0.1957)	(0.0801)
Cars	1.8843***	-0.0975***	-0.3039***	-0.6890***	-0.6240***	-0.0069**
	(0.2793)	(0.6331)	(0.4867)	(0.6511)	(0.7038)	(0.3577)
Trans	0.9869***	0.3093*	0.3103***	0.1641***	-0.0316***	-0.1482*
	(0.1111)	(0.2854)	(0.1594)	(0.2586)	(0.2557)	(0.1470)
Utils	0.7399***	-0.4228**	0.2907***	0.0221***	0.0676***	0.1644***
	(0.1190)	(0.2469)	(0.1948)	(0.2722)	(0.3053)	(0.1375)
Rtail	1.0059***	-0.2765***	-0.3774***	-0.1841***	-0.0119***	-0.1252*
	(0.0890)	(0.1932)	(0.1332)	(0.1783)	(0.2395)	(0.1279)
Finan	0.9615***	-0.0935***	0.6113***	-0.1563***	-0.2898***	-0.1333***

	(0.0581)	(0.1485)	(0.0506)	(0.1250)	(0.1463)	(0.0824)
Other	1.0216***	-0.0968***	-0.1370***	-0.0644***	-0.0568***	-0.0193*
	(0.0253)	(0.0676)	(0.0434)	(0.0599)	(0.0692)	(0.0335)
Obs.	38					
R2	0.7777					

Note: Standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1.

Finally, it increases FF5 by the momentum factor. According to their observations, FF6 functions just as well as FF5. All components are significant at the 1% level, indicating that market, size, value, momentum, profitability, and investment characteristics are very highly correlated with stock returns across the 17 sectors. Overall, this analysis concludes that conventional asset pricing models do a good job of explaining the reversals in the 17 US businesses. The performance of the model is marginally enhanced by the inclusion of RMW and CMA. The five-factor model has a little higher explanatory power than the conventional model.

3.3 Regression Results: Individual Industry

To investigate the validity of the model in individual industries, time series regressions were carried out for each industry, and the performance of the models was compared using the intercept term ai and adj-R2. The results presented in Table 6 indicate that the average ai value is close to zero, ranging from 0.01 (FF3) to 0.02 (CAPM). The mean ai value is slightly larger than the median, which suggests a slightly rightward skewing of the letter distribution. The positive skewness is confirmed by comparing the minimum and maximum values of ai. Additionally, the standard deviations of ai for these models are approximately the same (0.086-0.151).

The validity of the model was evaluated by focusing on the intercept, or alphas, of the models. According to asset pricing theory, MAVA should be zero. The more effective model is thought to be the one with the smallest MAVA. Table 4 shows that the intercept has a very low MAVA. It is evident that FF6 outperforms the CAPM with a MAVA of 0.066, which is approximately half that of the CAPM. This finding is consistent with Fama and French [8]. Moreover, the introduction of MOM, RMW and CMA, improves the original FF5 when looking at the intercept values. The majority of the variance in average returns between the 17 industries is captured by FF5. Overall, the empirical results suggest that the model holds validity in individual industries, and FF6 is a more efficient model than the CAPM. The findings also indicate that incorporating additional factors can improve the original FF5.

3.4 Robustness Analysis

The global economy was significantly impacted by COVID-19, with varying degrees of impact on different industries [9]. To assess the stability of 17 industries during this period, we analyzed a five-factor model with moment factors from 2020 to February 2023. Our regression analysis in Table 7 reveals that all factors in the five-factor model are statistically significant at the 1% level during the epidemic, except for SMB and MOM factors.

Most industries exhibit positive SMB coefficients, indicating numerous high-quality business opportunities despite the severe challenges of COVID-19. For instance, the food industry's SMB coefficient is negative from 1990 to 2023 (-0.0265), but positive from 2020 to 2023 (0.0310). This trend may be attributed to the surge in demand for delivery services in the US meal industry, with many small companies focusing on delivery businesses experiencing high returns on investment, according to Li & Wu [10]. It observes that four out of the 17 sectors are insignificant at the 5% level from Table 7, suggesting that FF5 does not fully explain the excess returns of small-cap stocks relative to large-cap stocks. Moreover, the MOM p-value is significant at the 5% level for only 10 industries during the COVID-19 period, failing to explain the absence of a correlation between past stock performance and future stock returns. One possible reason for this outcome could be the small sample size.

4 Conclusion

In conclusion, this study successfully examined the performance of the FF5 compared to the FF3 and CFFM models in explaining stock returns across various industries. By utilizing sector-level data from the NYSE, AMEX, and NASDAQ exchanges, the study shed light on the robustness of FF5 in different sectors. The findings of the study demonstrated that FF5 outperformed both FF3 and CFFM in capturing the changes in stock returns across industries. However, the effectiveness of FF5 varied among different sectors, with some industries exhibiting stronger performance than others.

These results contribute valuable insights into the applicability and validity of asset pricing models in different sectors of the economy. By highlighting the variations in model performance across industries, this study adds to the ongoing debate regarding the robustness and suitability of the FF5 model. Overall, this research enhances our understanding of the factors influencing stock returns within specific industries and provides valuable implications for investors, portfolio managers, and financial researchers in selecting appropriate asset pricing models for industry-specific analyses.

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