The Predicting Power of Asset Pricing Models during Market Turmoil

Xinyuan Liu^{1, a, *}, † Yunlong Ren^{2, b, *, †}

¹Shanghai Lixin university of Accounting and Finance, Shanghai, China

² University of California Santa Cruz, United State

*Corresponding author. Email: alxy_010120@163.com, byren43@ucsc.edu,

[†]*These authors contributed equally.*

ABSTRACT

This paper investigates the predictive return power of three asset pricing models during market turmoil: the CAPM, Fama-French 5 factor model, and q-factor model. We select two periods of market downturns: the 2008 financial crisis and the 2020 Covid period. The models are trained before these two periods and tested during the market turbulence. We specifically test the models on 10 stocks with different firm characteristics and compare their difference in performance. Out of three different asset pricing models, we find that the Fama-French five-factor model performs the best, with relatively small prediction error and standard deviation. When facing financial turmoil, the predictive ability of the three models decreases.

Keywords: Asset pricing model, Market turmoil, Stock market

1. INTRODUCTION

The economic downturn during the COVID-19 pandemic got us interested in testing the predictability of asset pricing models. We wanted to see how well predictive models can predict the market, and then we did the following survey. Scholars at home and abroad have studied the theory of the asset pricing model for a long time. Bernard and Thomas studied the drift after earnings release and found that the evidence could not be consistent with arguments based on risk measurement errors but with delayed price responses [1]. Fama and French showed that book-to-market ratio and market value could explain cross-sectional stock differences [2]. The evidence presented by Jegadeesh and Titman shows that the profitability of the relative strength strategy is not due to its systemic risk, and the results also show that relative strength profit cannot be attributed to the lead-lag effect caused by the delayed response of stock prices to common factors [3]. According to Loughran and Ritter, companies that issued stock between 1970 and 1990, whether they were initial public offerings or experienced stock offerings, as well as companies that performed search engine optimization, were poor long-term investments [4]. In the five years after issuance, the average annual return for listed companies is lower, significantly underperforming those with unissued shares. If the size and book ratio are unchanged, the issuing company's subsequent income is lower than that of the non-issuing company. Sloan points out that the extent to which current earnings performance extends into the future depends on the relative size of current earnings' cash and accrual components [5]. Dichev shows that bankruptcy risk does not compensate for higher returns, so a dilemma factor is unlikely to explain the impact of size and book to market [6]. Titman et al. found that companies that significantly increased their capital investment received negative returns after benchmark adjustment The negative [7]. non-capital investment/return relationship is stronger for companies with greater investment discretion (i.e., those with higher cash flows and lower debt ratios) and only becomes significant during periods when hostile takeovers are less common. Hirshleifer et al. proved that if the cumulative net operating income exceeds the cumulative free cash flow, the accounting appreciation exceeds the cash appreciation, the subsequent earnings growth will be weak. Daniel and Titman reveal that the future returns of stocks are strongly negatively correlated with "intangible" returns, and a company's past performance is positively correlated with the components of the past returns of stocks [8]. The evidence presented by Fama and French shows that when controlling the book-tomarket ratio and expected investment, the company with

higher profitability will have a higher expected return, as will the company with a higher book-to-market ratio. Cooper et al. found that the higher the asset growth rate was, the higher the subsequent annual average riskadjusted return was [9]. Total asset growth dominates other standard variables that predict future earnings. Xing provides evidence that cross sections of portfolio companies with lower investment growth rates (working groups) or low investment-to-capital ratios have significantly higher average returns than those with high working groups or high investment-to-capital ratios despite value effects despite Q-theory criteria Quasi. Novy-marx pointed out that the profitability measured by total profits and assets showed that the return rate of profitable companies was significantly higher than that of unprofitable companies [10]. Profitable companies have longer cash flow and lower operating leverage. Furthermore, we found a paper that was most related to our studies. The goal of Santana and Rathke is to compare the performance of the statistical factor asset pricing model with the Fama-French-Carhart 4 factor model [11]. They conducted principal component analysis (PCA) using data of B3 listed companies from 2001 to 2015 to extract potential risk factors and examine the ability of these two models to explain asset returns over time series and crossover series. Partial dimensions. Then they find that the statistical factor model produces statistically significant outlier returns in time series analysis, while the four-factor model does not. Neither model produced significant outlier returns in the cross-sectional dimension, but neither model produced a positive risk premium. If Santana and Rathke consider different times and assets, they will find similar results. Thus, although the four-factor model performs slightly better in this set of tests, neither model can be considered to fully explain the expected returns of Brazilian stock market assets. Hou, Xue and Zhang (2015) constructed the q-factor model consisting of the market factor, a size factor, an investment factor, and a profitability factor that explains the average stock returns. With few exceptions, the qfactor model outperforms the 3-factor model by Fama & French (1993) and the 4-factor model by Carhart (1997) as it summarized the cross section of average stock returns. The three stock-market factors include the overall index performance, firm size and book-to-market equity. There are also two bond-market factors related to maturity and default risks. Stock returns correlate due to the relationship between stock-market and bond returns, excluding low credit-grade corporations. The bondmarket factors capture the common variation in bond returns. In 2015, the two authors, Fama & French, proposed a five-factor model directed at capturing the size, value, profitability, and investment patterns in average stock returns, outperforming the three-factor model. However, it fails to capture the low average returns on small stocks. Using a sample free of survivor bias, Carhart (1997) demonstrated that common factors in stock returns and investment expenses could almost

explain persistence in equity mutual funds' mean and risk-adjusted returns. Hou et al. (2020) tested all the factors models in the past and found that most anomalies fail to hold up to currently acceptable standards for empirical finance. Stambaugh & Yuan (2017) announced a four-factor model with two more mispricing factors, which they think was better than notable four- and fivefactor alternative models. Moreover, the size factor revealed a small-firm premium nearly twice the usual estimate.

Hou et al., n.d. (2014) compared the q-factor model and the five-factor model conceptually and empirically. Four concerns cast doubt on the five-factor model: The internal rate of return often correlates negatively with the one-period-ahead expected return; the value factor seems redundant in the data; the expected investment tends to correlate positively with the one-period ahead expected return, and past investment is a poor proxy for the expected investment. The conclusion is that the fourfactor q-model outperforms the five-factor model, especially in capturing price and earnings momentum and profitability anomalies.

Compared with our country's research, China's stock market is strictly controlled, so domestic scholars have little research on the assets model. Based on the American stock market, we mainly study the articles of foreign scholars. Based on these, since there are few investigations in the context of the epidemic or unstable economic situations, such as natural disasters or financial crises. So, we want to further compare the 5-factor model with previous studies and analyze the shortcomings of the 5-factor method.

2. DATA AND METHOD

2.1. Data

We select ten random companies' real stock market returns, including Apple, Google, Microsoft, Baidu, Amazon, Intel, Dell, eBay, Pepsi, and Nike. The numbers are from S&P 500. The periods we choose are time from the time when the ten companies entered the stock market to the 2007 financial crisis, the 2020 covid-19 period and 2018, which we select randomly.

2.2. Method L

2.2.1. The Fama-French 5 factors model

Fama and French have proposed a three-factor model, arguing that the excess returns of stocks can be jointly explained by market risk, market value risk and book value ratio risk [12]. Later, they found that in addition to the above three risks, profitability and investment factors can also bring the excess returns of individual stocks. Therefore they proposed the new five factors model [13].

 R_{it} = the return on the stock portfolio for period t, R_{Ft} = the risk-free return, R_{Mt} = the value-weighted market return, SMB_t = the return on small stock portfolio minus the return on a big stock portfolio, HML_t = the high book-to-market ratio minus low book-to-market ratio orthogonalized, RMW_t = stands for robust operating profitability portfolios minus weak operating profitability portfolios, CMA_t = conservative investment portfolios minus aggressive investment portfolios. The error term is distributed as the Normal.

2.2.2. q-factor model

The q-factor model, which includes four risk factors, summarizes the cross section of average stock returns [14]. The first is the market factor, which encompasses both macroeconomic and overall market risk premiums. The second is the size factor that represents the market capitalization of a firm. The third factor is the investment factor. Investment means physical investment rather than a financial investment, such as building a factory or buying new equipment. The last factor is profitability. Earnings are the accounting profit ratio, which is equal to profit divided by book capital.

 $E[r^{i}] - r^{f} = \beta^{i}_{MKT} E[MKT_{t}] + \beta^{i}_{ME} E[r_{ME}] + \beta^{i}_{\frac{I}{A}} E[r_{\frac{1}{A}}] + \beta^{i}_{ROE} E[r_{ROE}] \dots (2)$

 $E[r^i] - r^f$ = the expected return of an asset in excess of the risk-free rate, MKT= the market excess return, r_{ME} = the difference between the return on a portfolio of small size stocks and the return on a portfolio of big size stocks, $r_{\frac{1}{A}}$ = the difference between the return on a portfolio of low investment stocks and the return on a portfolio of high investment stocks, r_{ROE} = the difference between the return on a portfolio of high profitability (return on equity, ROE) stocks and the return on a portfolio of low profitability stocks, $E[MKT_t]$, $E[r_{ME}]$, $E[r_{\frac{1}{A}}]$ and $E[r_{ROE}]$ are expected factor premiums, and β_{MKT}^i , β_{ME}^i , $\beta_{\frac{1}{A}}^i$ and β_{ROE}^i are the factor loadings on MKT, r_{ME} , $r_{I/A}$ and r_{ROE} .

3. Results and discussion

We first train the model on the monthly return data before the market downturn, then we test the predictability of the trained model on the period of market turmoil. After doing the regression, we focus on the predicting power of the three models. Then we train the model by regression each stock's monthly return on the returns of risk factors in the three assets pricing model. Next, we calculate the absolute value of the difference between the predicted price and the real return, which is defined as prediction error. By analyzing the error, we can compare the predicting ability of the three models and conclude which one performs the best during the downturn period in the market.

Panel A								
	Fama-French 5 factor model(during crisis)							
	Intercept	rm	SMB	HML	RMW	CMA		
Apple	0.0495	1.066	0.3328	-0.1541	-0.0955	-1.535		
Google	0.0449	1.0749	-0.0229	-0.8888	-0.4316	-2.8244		
Microsoft	0.0167	1.0542	-0.0415	-0.8878	0.5319	-1.1329		
Baidu	0.0405	1.9647	-3.0305	-3.4688	1.3963	-1.4323		
Amazon	0.0488	2.0959	-0.9535	-1.366	-0.1173	-0.2392		
Intel	0.0121	1.3695	-0.4299	-1.1609	-0.2256	0.5409		
Dell	0.0182	1.0624	0.1702	-0.4858	0.5092	-1.7068		
Pepsi	0.0031	1.0023	-0.157	-0.2452	0.6359	0.5948		
Nike	0.0101	1.1558	-0.3748	0.4936	0.8599	-0.4039		

Table 1. The result of regression

-0.4402

-1.2189

0.2652

0.4715

0.0402

2.2501

eBay

	q-factor mod	del(during crisis))		Capm(durin	ıg crisis)
Intercept	R_MKT	R_ME	R_IA	R_ROE	Intercept	MKT
0.0499	1.1134	0.0275	-1.6023	-0.2574	0.0413	1.7027
0.0486	1.1455	-0.2661	-1.935	-0.8237	0.0468	1.2983
0.02	0.9446	-0.5131	-1.5439	-0.3148	0.0092	1.4795
0.0389	2.6021	-3.8938	-2.3233	1.7466	0.0656	0.9425
0.0482	2.2734	-0.8723	-1.4808	-0.0635	0.0377	2.6328
0.0176	1.1613	-0.5537	-0.3625	-1.114	0.0069	1.7107
0.0221	0.9185	-0.4506	-1.8394	-0.3267	0.0102	1.5525
0.0017	1.0228	-0.0792	0.4792	0.6687	0.0076	0.5681
0.0091	1.178	-0.6136	0.5516	0.7381	0.0135	0.6076
0.0434	2.1223	-0.5664	-0.2368	-0.5301	0.0356	2.4171

Panel B

Fama-French 5 factor model(pre-pandemic)
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	Intercept	rm	SMB	HML	RMW	СМА
Apple	0.0267	1.1989	0.2098	-0.5443	0.2414	-1.0592
Google	0.0123	1.0989	-0.434	-0.1046	0.1667	-1.2175
Microsoft	0.0113	0.9805	-0.283	-0.1635	-0.0247	-1.2283
Baidu	0.0155	1.4249	0.1493	-0.2108	-0.5855	-1.1634
Amazon	0.0286	1.5514	-0.726	-0.9687	-0.3419	-0.7535
Intel	0.0058	1.0898	-0.3239	-0.3873	-0.6103	-0.0544
Dell	0.0067	1.1356	0.1203	-0.1463	0.1136	-1.412
Pepsi	0.0023	0.7437	-0.2932	-0.169	0.3887	0.4576
Nike	0.0099	0.9305	-0.2608	0.365	0.8033	-0.4491
eBay	0.0175	1.5841	-0.3574	-0.3774	-0.3894	-0.2822

q-factor model(pre-pandemic)

Capm(pre-pandemic)



	Intercept	R_MKT	R_ME	R_IA	R_ROE	Intercept	Mk	ΚT
	0.0283	1.1655	-0.0341	-1.3855	-0.0622	0.0252	1.35	571
	0.0127	1.1201	-0.52	-0.8959	0.0123	0.014	0.98	388
	0.0114	1.0139	-0.4796	-1.1197	-0.1658	0.0078	1.11	191
	0.0154	1.3667	0.1475	-1.2212	-0.3235	0.0145	1.51	171
	0.0299	1.548	-0.8053	-1.6782	-0.1516	0.0248	1.65	54
	0.0075	0.9959	-0.405	-0.4797	-0.6752	0.0028	1.2	15
	0.0072	1.1558	-0.1723	-1.2261	-0.1857	0.0024	1.34	179
	0.0024	0.7825	-0.2138	0.3459	0.476	0.0051	0.5	27
	0.009	1.0483	-0.4248	0.4008	0.5449	0.0119	0.7	'19
	0.0192	1.4864	-0.4559	-0.5713	-0.5577	0.0146	1.66	579
_	Panel C							
-								
			Fa	ama-French	5 factor mo	del		
_		Intercept	Fa	ama-French SMB	5 factor mo HML	del RMW	СМА	
_	Apple	Intercept 0.0281	Fa rm 1.1605	ama-French SMB 0.2771	5 factor mo HML -0.5164	del RMW 0.2351	CMA -1.2301	
_	Apple Google	Intercept 0.0281 0.0139	Fa rm 1.1605 1.214	ama-French SMB 0.2771 -0.4653	5 factor mo HML -0.5164 -0.3748	del RMW 0.2351 0.1912	CMA -1.2301 -1.2234	
_	Apple Google Microsoft	Intercept 0.0281 0.0139 0.0115	Fa rm 1.1605 1.214 1.0254	ama-French SMB 0.2771 -0.4653 -0.2295	5 factor mo HML -0.5164 -0.3748 -0.1345	del RMW 0.2351 0.1912 0.0318	CMA -1.2301 -1.2234 -1.307	
_	Apple Google Microsoft Baidu	Intercept 0.0281 0.0139 0.0115 0.0168	Fa rm 1.1605 1.214 1.0254 1.7306	ama-French SMB 0.2771 -0.4653 -0.2295 -0.08	5 factor mo HML -0.5164 -0.3748 -0.1345 -0.3971	del RMW 0.2351 0.1912 0.0318 -0.0697	CMA -1.2301 -1.2234 -1.307 -1.1365	
-	Apple Google Microsoft Baidu Amazon	Intercept 0.0281 0.0139 0.0115 0.0168 0.0323	Fa rm 1.1605 1.214 1.0254 1.7306 1.6378	ama-French SMB 0.2771 -0.4653 -0.2295 -0.08 -0.6924	5 factor mo HML -0.5164 -0.3748 -0.1345 -0.3971 -1.1303	del RMW 0.2351 0.1912 0.0318 -0.0697 -0.2104	CMA -1.2301 -1.2234 -1.307 -1.1365 -0.759	
	Apple Google Microsoft Baidu Amazon Intel	Intercept 0.0281 0.0139 0.0115 0.0168 0.0323 0.008	Fa rm 1.1605 1.214 1.0254 1.7306 1.6378 1.1465	ama-French SMB 0.2771 -0.4653 -0.2295 -0.08 -0.6924 -0.3255	5 factor mo HML -0.5164 -0.3748 -0.1345 -0.3971 -1.1303 -0.4528	del RMW 0.2351 0.1912 0.0318 -0.0697 -0.2104 -0.5618	CMA -1.2301 -1.2234 -1.307 -1.1365 -0.759 -0.0237	
_	Apple Google Microsoft Baidu Amazon Intel Dell	Intercept 0.0281 0.0139 0.0115 0.0168 0.0323 0.008 0.0084	Fa rm 1.1605 1.214 1.0254 1.7306 1.6378 1.1465 1.2179	ama-French SMB 0.2771 -0.4653 -0.2295 -0.08 -0.6924 -0.3255 0.227	5 factor mo HML -0.5164 -0.3748 -0.1345 -0.3971 -1.1303 -0.4528 -0.1056	del RMW 0.2351 0.1912 0.0318 -0.0697 -0.2104 -0.5618 0.2366	CMA -1.2301 -1.2234 -1.307 -1.1365 -0.759 -0.0237 -1.5818	
_	Apple Google Microsoft Baidu Amazon Intel Dell Pepsi	Intercept 0.0281 0.0139 0.0115 0.0168 0.0323 0.008 0.0084 0.0022	Fa rm 1.1605 1.214 1.0254 1.7306 1.6378 1.1465 1.2179 0.7853	ama-French SMB 0.2771 -0.4653 -0.2295 -0.08 -0.6924 -0.3255 0.227 -0.2819	5 factor mo HML -0.5164 -0.3748 -0.1345 -0.3971 -1.1303 -0.4528 -0.1056 -0.2052	del RMW 0.2351 0.1912 0.0318 -0.0697 -0.2104 -0.5618 0.2366 0.4473	CMA -1.2301 -1.2234 -1.307 -1.1365 -0.759 -0.0237 -1.5818 0.4945	
_	Apple Google Microsoft Baidu Amazon Intel Dell Pepsi Nike	Intercept 0.0281 0.0139 0.0115 0.0168 0.0323 0.008 0.0084 0.0084 0.0022 0.009	Fa rm 1.1605 1.214 1.0254 1.7306 1.6378 1.1465 1.2179 0.7853 0.9823	ama-French SMB 0.2771 -0.4653 -0.2295 -0.08 -0.6924 -0.3255 0.227 -0.2819 -0.2583	5 factor mo HML -0.5164 -0.3748 -0.1345 -0.3971 -1.1303 -0.4528 -0.1056 -0.2052 0.3939	del RMW 0.2351 0.1912 0.0318 -0.0697 -0.2104 -0.5618 0.2366 0.4473 0.8539	CMA -1.2301 -1.2234 -1.307 -1.1365 -0.759 -0.0237 -1.5818 0.4945 -0.4598	
-	Apple Google Microsoft Baidu Amazon Intel Dell Pepsi Nike eBay	Intercept 0.0281 0.0139 0.0115 0.0168 0.0323 0.008 0.0084 0.0084 0.0022 0.009 0.0197	Fa rm 1.1605 1.214 1.0254 1.7306 1.6378 1.1465 1.2179 0.7853 0.9823 1.666	ama-French SMB 0.2771 -0.4653 -0.2295 -0.08 -0.6924 -0.3255 0.227 -0.2819 -0.2583 -0.4029	5 factor mo HML -0.5164 -0.3748 -0.1345 -0.3971 -1.1303 -0.4528 -0.1056 -0.2052 0.3939 -0.4641	del RMW 0.2351 0.1912 0.0318 -0.0697 -0.2104 -0.5618 0.2366 0.4473 0.8539 -0.3466	CMA -1.2301 -1.2234 -1.307 -1.1365 -0.759 -0.0237 -1.5818 0.4945 -0.4598 -0.196	

q-factor model					Capn	n
Intercept	R_MKT	R_ME	R_IA	R_ROE	Intercept	MKT
0.0295	1.1226	-0.0065	-1.489	-0.1498	0.0248	1.3832
0.0146	1.2055	-0.5674	-1.1569	0.0604	0.015	1.045

0.0119	1.0548	-0.4611	-1.1644	-0.1936	0.007	1.2014
0.0186	1.6473	-0.2159	-1.0548	-0.3557	0.017	1.6888
0.0336	1.6312	-0.7924	-1.8345	-0.2043	0.0263	1.8141
0.0099	1.0644	-0.4012	-0.5226	-0.7254	0.0041	1.3207
0.0098	1.2086	-0.1993	-1.2938	-0.2584	0.003	1.4538
0.0019	0.8063	-0.1999	0.3424	0.5377	0.0051	0.5306
0.0084	1.0591	-0.4585	0.4153	0.611	0.0117	0.6993
0.0221	1.5433	-0.5212	-0.5512	-0.6981	0.0159	1.7796

Caption: The following panels are the regressions of the three different models. The Y in the regression is the stock market return, while the Xs are the factors of the three models. Panel A is the regression done by using the data before July 2007 at the beginning of the financial crisis. Panel B is the regression done by using the data before January 2020, when the pandemic of COVID-19 broke out. Panel C is the regression done by using a random date (we choose the data before December 2018). As Table1 shows, Fama-French 5 factor model shows more data, and each data is close to zero.

	error(during crisis)			sd of real data(during	
	FF 5 factors	q-factor	capm	crisis)	
Apple	1.6946	1.7436	1.829	0.1376	
Google	1.597	1.8817	2.0242	0.1128	
Microsoft	1.3667	1.3692	1.3962	0.0828	
Baidu	4.2539	3.7503	3.0738	0.1901	
Amazon	2.1693	2.7724	3.0921	0.1331	
Intel	1.3933	1.5318	1.2373	0.0968	
Dell	2.3336	2.445	2.089	0.1313	
Pepsi	1.0781	0.9447	0.9938	0.0619	
Nike	1.0577	1.3379	1.2848	0.0878	
eBay	1.7222	1.6185	1.6946	0.1354	
sd of predicted data(during crisis)					
FF	5 factors	q-fact	tor	capm	
().0846	0.087	73	0.115	
().0978	0.103	4	0.0877	

Table 2. The errors and the deviations

0.067	0.0723	0.1	
0.1905	0.1623	0.0636	
0.12	0.1475	0.1778	
0.0756	0.107	0.1155	
0.0768	0.0734	0.1048	
0.0535	0.05	0.0384	
0.0779	0.0538	0.041	
0.1244	0.1515	0.1632	

Panel B

	erroi	sd of real data(pre-		
	FF 5 factors	q-factor	capm	pandemic)
Apple	0.9472	0.7499	0.7174	0.1052
Google	0.8175	0.5245	0.4839	0.0799
Microsoft	0.6834	0.593	0.6401	0.0583
Baidu	2.0907	1.5837	1.551	0.1691
Amazon	0.9114	1.0379	1.013	0.0903
Intel	1.0731	1.0216	1.0109	0.097
Dell	0.9708	0.7953	0.7433	0.0923
Pepsi	0.433	0.3059	0.2532	0.0602
Nike	0.9158	0.7535	0.6095	0.0759
eBay	1.2478	1.2005	1.0893	0.1114

sd of predicted data(pre-pandemic)

FF 5 factors	q-factor	capm
0.0843	0.0941	0.1056
0.0759	0.0776	0.0773
0.0705	0.0771	0.0908
0.1152	0.1327	0.1304
0.1016	0.1149	0.136
0.0656	0.0945	0.1002
0.0905	0.0946	0.1077

0.0509	0.0455	0.0393
0.0857	0.0622	0.0553
0.0979	0.1257	0.1345

Panel C

	error(normal time)			sd of real data(normal
	FF 5 factors	q-factor	capm	time)
Apple	1.364	1.3431	1.1359	0.0904
Google	1.2778	1.0854	0.9001	0.0698
Microsoft	0.7655	0.8316	0.9419	0.0536
Baidu	2.5906	2.5693	2.4714	0.1468
Amazon	1.5878	1.7733	1.6977	0.0828
Intel	1.4373	1.6962	1.5979	0.0877
Dell	1.8296	1.8194	1.7555	0.1009
Pepsi	0.6271	0.649	0.5726	0.0426
Nike	1.085	1.19	1.0407	0.0733
eBay	1.5817	1.7378	1.6789	0.1018
				•

sd of predicted data(normal time)

FF 5 factors	q-factor	capm
0.0754	0.0781	0.8373
0.069	0.0681	0.0633
0.0623	0.0651	0.0727
0.1012	0.1065	0.1022
0.0854	0.0981	0.1098
0.0563	0.0752	0.0799
0.0841	0.0803	0.088
0.0429	0.0375	0.0321
0.0694	0.048	0.0423
0.0865	0.1007	0.1077

Caption: The table shows the error of the three models (Fama-French 5 factors model, q-factor model and the CAPM) when predicting the stock market returns in three periods. The periods are the financial crisis, the pandemic of COVID-19 and a random date (we choose December 2018). The equation of the error is sum(abs(predicted return - real return)). The standard deviation of real data and the predicted data in three time periods are also calculated.

This figure shows the Fama-French Five factor model's prediction and the actual data during the financial crisis period. The prediction is made by regressing the stock return on the returns of five factors and obtaining the predicted value based on the factor return during the financial crisis period.



Figure 1. Predictions of Fama-French 5 factors Model during 2008 Crisis

This figure shows the prediction of the Fama-French 5 factors Model and the actual data during the financial crisis period. The prediction is made by regressing the stock return on the market's returns and obtaining the predicted value based on the market return during the financial crisis period.



Figure 2. Predictions of q factor Model during 2008 Crisis

This figure shows the prediction of the q factor model and the actual data during the financial crisis period. The prediction is made by regressing the stock return on the returns of q factors and obtaining the predicted value based on the factor return during the financial crisis period.





Figure 3. Predictions of CAPM Model during 2008 Crisis

This figure shows the prediction of the CAPM Model and the actual data during the financial crisis period. The prediction is made by regressing the stock return on the market's returns and obtaining the predicted value based on the market return during the financial crisis period.



Figure 4. Predictions of Fama-French Five factor Model during Pandemic

This figure shows the prediction of the Fama-French Five factor model and the actual data during the Pandemic. The prediction is made by regressing the stock return on the returns of five factors and obtaining the predicted value based on the factor return during the Covid period.





Figure 5. Predictions of q factor Model during Pandemic

This figure shows the prediction of the q factor model and the actual data during Pandemic. The prediction is made by regressing the stock return on the returns of q factors and obtaining the predicted value based on the factor return during the Covid period.



Figure 6. Predictions of CAPM Model during Pandemic

This figure shows the prediction of the CAPM Model and the actual data during Pandemic. The prediction is made by regressing the stock return on the market's returns and obtaining the predicted value based on the market return during the Covid period.



Figure 7. Predictions of Fama-French Five factor Model during Random period

This figure shows the Fama-French Five factor model's prediction and the actual data during a random period (2018). The prediction is made by regressing the

stock return on the returns of five factors and obtaining the predicted value based on the factor return during the normal period.







Figure 8. Predictions of q factor Model during Random period

This figure shows the prediction of the q factor model and the actual data during a random period (2018). The prediction is made by regressing the stock return on the returns of q factors and obtaining the predicted value based on the factor return during the normal period.



Figure 9. Predictions of CAPM Model during Random period.

This figure shows the prediction of the CAPM Model and the actual data during a random period (2018). The prediction is made by regressing the stock return on the market's returns and obtaining the predicted value based on the market return during the normal period.

4. CONCLUSION L&R

This paper provides evidence that the Fama-French five factor is a particularly valuable predictor of asset returns. Regression was used to analyze and calculate the financial crisis in 2008, the epidemic in 2020, and the randomly selected data of several years by using 24monthly data. Because the prediction error of the Fama-French 5 factor model was low, and its standard deviation was the lowest in the three time periods. Therefore, we conclude that the Fama-French five factor is the model with the best predictive power.

There are also more things we can conclude from the paper. First, the three models we choose may not predict the companies from other nations. Errors and the standard deviations of the Chinese company Baidu are the highest among the 10 companies in three models in the three chosen periods. Second, there are great differences between the predicted returns and the real returns. Moreover, when facing financial turmoil, the predictive ability of the three models decreases. According to the graphs, the lines of actual returns and predicted returns can almost coincide during a normal time. The two lines have significant disparity by comparison, which means the model cannot always predict the downturn. Therefore, we also drew several images under the trend of stable economic development, from which we can see that the predicted trend of FF5 is closest to the actual trend. Therefore, we can conclude that the Fama French 5 Factor Model has the strongest forecasting ability.

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