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The Empirical Explanatory Power of CAPM and the Fama and French Three-Five Factor Models in the Moroccan Stock Exchange

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Abstract: This study empirically tests and compares the performances of three famous financial asset valuation models in the Moroccan stock exchange: CAPM, the Fama and French three-factor model, and the Fama and French five-factor model. Our sample considers monthly data covering the sample period of July 2002 to June 2020. The main findings reveal that the GRS test typically rejects each of the examined model. On the basis of our analysis, we find that the value effect is more pronounced than the size effect. However, profitability and investment effects are almost absent. Regarding the factor spanning tests, the results show that the value factor was not redundant. Beyond this, the size and investment factors are the redundant factors. In Morocco, the market factor is the most powerful factor, perhaps assisted by value and profitability factors. Although the CAPM performs poorly in capturing the variation in Moroccan returns, the market factor continues to play an important role, even after adding other factors. Overall, all the tested models were improved slightly, but leave part of the variation in Moroccan stock returns unexplained.

Keywords: asset pricing models; CAPM; Fama and French three-factor model (1993); Fama and French five-factor model (2015); Moroccan stock exchange; emerging market

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1. Introduction

There is a keen interest in the finance literature in the comprehension and explication of the relationship between risks and returns. Scientific researchers are particularly interested in modeling the relation between the return that investors expect to earn from their placements in stocks and the risk level associated with their investments.

The work of Markowitz (1952) marked the starting point of modern theoretical developments underlining the risk factors of expected returns. The original model, as theorized simultaneously and independently by Sharpe (1963, 1964), Lintner (1965) and Mossin (1966), includes only the market factor in explaining asset returns; this is the Capital Asset Pricing model (hereafter CAPM). The latter was and remains a guide for academics and practitioners given its simplicity and rigorous construction. However, the model has shown itself to be relatively empirically flawed.

The desire to revisit the model as a response to its imperfections has spurred several researchers into providing a variety of new empirical models. The most discussed financial asset valuation model is assigned to Fama and French (1992, 1993). Entitled the Fama and French three-factor (hereafter, FF3F) model (1993), it embraces others risk factors in addition to the CAPM beta, such as the mimicking returns for the size factor and the mimicking returns for the book-to-market factor. Despite the empirical success of the FF3F model, some studies have deemed it to be incomplete, and documented the improvements achieved with additional factors. Prompted by these conclusions, Fama and French (2015) put forward a new multi-index asset pricing model, the Fama and French five-factor (hereafter FF5F) model. The authors added two other factors to their traditional model (FF3F model): the investment and profitability factors.

The studies conducted on the risk–return relationship, especially those that are interested in the validity of the Fama and French models, first tend to investigate developed markets, before turning to emerging markets, in particular Asian markets such as China, India, Malaysia, Thailand, etc. However, the results show some discrepancies between the markets. The emerging markets have specific characteristics that can challenge established asset pricing models (Zaremba and Czapkiewicz 2017; Alrabadi and Alrabadi 2018 and Ragab et al. 2020). Very few studies have investigated African emerging markets (apart from South Africa), and specifically North African markets, where there is a remarkable gap. Our study is particularly interested in one of these markets: the Moroccan market. The literature regarding the application of asset pricing models in this market is sparse. Only two studies so far have been interested in the Moroccan context. Aguenaou et al. (2011) tested the explanatory power of the FF3F model and Tazi et al. (2022) compared the applicability of the FF3F model and the Carhart four-factor model[1] (hereafter, C4F model). Our paper represents a pioneering comparative analysis that offers an out-of-sample test, over a period from July 2002 to June 2020, with the following objectives:

- To test the ability of the CAPM, FF3F and FF5F models to capture the variations in Moroccan stock returns;
- To compare the performance of the three models in order to determine which model outperforms the others in explaining Moroccan returns;
- To examine redundant factors, with the purpose of finding out which factors explain the greater part of Moroccan stock returns.

Our interest in the Moroccan market comes from the fact that it was the first stock exchange in the Maghreb and West Africa, and the second in Africa, behind Johannesburg (EIB 2022)[2]. Since its creation in 1929, the Moroccan stock exchange has made continuous efforts to promote its position among the most innovative stock exchanges on the African continent. In 2010, the Moroccan market joined the World Federation of Exchanges (WFE), and thus became its 52nd member; the fourth Arab stock exchange and the fourth African stock exchange to do so. Moreover, the Moroccan stock exchange was ISO 9001-Version 2008-certified from 2011 to 2014[3]. In addition, the Moroccan financial market was the first African financial hub established through the "Casablanca Finance City" (CFC), and has maintained its top position on the African continent since 2016, according to the Global Financial Centers Index (GFCI) ranking.

Following the Fama and French (1993, 2015) methodology, our paper's results seem to generally confirm the superiority of the FF5F model in explaining Moroccan stock returns. However, as it is incomplete, the model leaves unexplained the variation in Moroccan stock returns. Inconsistent with Fama and French's results for developed markets, the value factor is not redundant. Here, both size and investment factors are the redundant factors. In Morocco, the market factor is the most powerful factor, perhaps aided by value and profitability factors.

The results of the study make a primary contribution to the literature on African emerging markets, in particular those of North Africa. Henceforth, we should better define the return–risk relation in this market, which would help us to measure with more precision the risk of Moroccan markets, and would have considerable managerial implications, particularly in terms of portfolio management and the assessment of the cost of equity of Moroccan companies.

The remainder of our study is structed along these lines: First, we undertake a short review of the empirical literature. Then, we describe the study's data and methodology. Finally, we summarize and discuss the results of empirical tests.

2. Literature Review

In accordance with the theoretical advances of Markowitz (1952), Sharpe (1964) developed the CAPM, which is the basis of standard financial theory. Known as the one-factor model, it asserts that the expected asset return is explained by the single systematic factor beta (the market factor). However, Roll (1977) criticizes the CAPM's assumptions. For this author, the hypotheses of the model are idealistic. In addition, several empirical tests have revealed little support, such that the CAPM leaves stock returns unexplained. Despite its shortcomings, the model is still being considered as the fundamental milestone for all succeeding financial asset valuation models. Fama and French (1992, 1993) developed a new model by including in the CAPM beta two further factors, the size and the value premiums, in its reply to the two popular anomalies introduced, respectively, by Banz (1981) and Stattman (1980). The Fama and French three-factor model (1993) (hereafter FF3F) has been used in describing the variation in stock returns in developed markets, and many studies have confirmed the significant role of the two additional factors in explaining stock returns (e.g., Fama and French 2008; Bhatnagar and Ramlogan 2012; Walkshäusl and Lobe 2014). Identical findings have also been acquired in studies carried out in emerging markets. Bundoo (2008) emphasized the robustness of the FF3F in describing the variation in Mauritius' returns even when taking into account time-varying betas. Pasaribu (2009) concluded a considerable increase in the explanatory power of FF3F compared to CAPM using data from the Brazilian market. For their part, Xie and Qu (2016) concluded that the FF3F can satisfactorily explain the variation in China's Shanghai stock exchange. Ajlouni and Khasawneh (2017) and Shah et al. (2021) derived similar results to Pasaribu (2009) when their models were tested on Amman and Pakistan's markets, respectively.

Furthermore, the FF3F model can span a number of areas, explaining its position in the literature. Vidal-García et al. (2018) tested the short-term market efficiency of the mutual fund industry using the CAPM, FF3F and C4F models. Additionally, Boubaker et al.'s (2018) study contributes to the literature on the FF3F model by examining the risk factors that best capture the financial distress risk in the French stock market.

Despite its success amongst academics and practitioners, many studies offer evidence that the FF3F model may be incomplete. In other words, adding the other two factors to the traditional CAPM model leads to insufficient improvements in capturing all the variations in stock returns. The important role of the investment factor and the profitability factor in describing the average stock returns is emphasized, respectively, by Titman et al. (2004) and Novy-Marx (2013). Motivated by the authors' conclusions, Fama and French (2015) expanded the FF3F model and introduced two further factors to take into account profitability and investment patterns. Therefore, the Fama and French five-factor (hereafter FF5F) model outperforms the traditional FF3F model. Fama and French (2017) compared the abilities of both their models to explain returns in an international sample of 23 developed markets in Asian, Europe and North America. Although formal tests may commonly reject the FF5F model, the results highlight the prevalence of the model over the FF3F model in describing returns in these regions. Furthermore, Lin (2017) confirmed the robustness of the FF5F model in China's stock market. Leite et al. (2018) derived similar results when the model was tested in Chinese, Indian, Malay and Thai markets.

However, the FF5F shows little sensitivity to some markets' average equity returns in other studies. Chiah et al. (2016) reported that, despite the preeminence of the FF5F model over the FF3F model, it could not explain all the variations in Australian returns. Contrary to Lin (2017) and Leite et al. (2018), Guo et al. (2017) found a marginal contribution of the investment factor in explaining Chinese returns. In Poland, Zaremba et al. (2019) compared four popular factor models—CAPM, the FF3F model, the C4F model and the FF5F model. As a result, the authors concluded that the four-factor model is the most appropriate model for Polish market returns. From the same perspective, Foye and Valentinčič (2020) conducted a comparative test of the competing model on the Indonesian stock exchange. Despite the improvement induced by the FF5F model compared to the FF3F model, the study's results are not very encouraging as regards using the FF5F model in Asian countries, which confirms the findings of his previous study (Foye 2018). Similarly, Dolinar et al. (2020) noticed that the FF5F model works more effectively than the FF3F model, but only marginally.

Approximately half of the variation in Croatian stock returns remains unexplained by the model.

Regarding the African emerging markets, the literature on testing the explanatory power of asset pricing models is sparse. While studying the Egyptian market, Ragab et al. (2020) found that despite the superiority of the FF5F model over competing models, it provides incomplete explanations of the variations in returns. On the South African market, Charteris et al. (2018) found that the FF5F model performed better compared to the FF3F and C4F models. Similarly, Cox and Britten (2019) emphasized the superiority of the FF5F model over the FF3F model, as well as other factor combinations, on the Johannesburg Stock Exchange. However, neither study's results show the same magnitude as those reported by Fama and French (2015).

To our knowledge, in the case of the Moroccan market, there is as yet no empirical study comparing the three competing models (CAPM, FF3F and FF5F models). Aguenaou et al. (2011) tested the explanatory power of the FF3F model. However, inconsistent with Fama and French's (1993) methodology, the authors include both non-financial and financial companies (banks, financial institutions, and assurance companies) in their study sample. As Fama and French (1993) argued, those stocks are excluded because of their high financial leverage. Tazi et al. (2022) investigated whether the FF3F model or the C4F model performs better in capturing the variation in the Moroccan stock exchange. Their findings show that both models are partially effective in predicting Moroccan stock returns.

3. Data and Variables Description

3.1. Data Selection

Asset pricing tests use monthly returns and cover the period from July 2002 to June 2020. The data were obtained from the Refinitiv database augmented by the Moroccan stock exchange website. To qualify for the sample, companies should provide market capitalization (market value of equity) and accounting data for December of the year $t - 1$, where t corresponds to the factors' and test portfolios' defined year. In conformity with the literature, we exclude financial services stocks and firms with negative book values in terms of equity. The sample consists of 52 Moroccan companies. Given the availability of data, the considered sample is not cylindrical. The number of stocks observed increases from year to year.

In order to calculate the stock returns on a monthly basis, we have included capital gains and dividends yields. We use all stocks in the sample and we consider their value-weighted returns as a measure of the market rate. The study uses, as a proxy for the risk-free rate, the monthly rate equivalent to 13 weeks Treasury's bill rate, as available on the Bank Al-Maghrib's (the central bank of the Kingdom of Morocco) website (Akhtaruzzaman et al. 2014; Chai et al. 2019).

The basic variables included in our tests are the size (market capitalization), the B/M ratio, the operating profitability ratio (hereafter OP) and the investment (hereafter Inv).

We define market capitalization as the product of the adjustment of the closing price for the month and the number of shares outstanding. Concerning the book-to-market ratio, this is estimated as the reverse of the market value-to-book variable obtained from the Refinitiv database. The OP is the difference between the annual revenue and the cost of sales, selling, general and administrative expenses and interest expenses, all over the book value of equity, and it is identified in December of year $t - 1$. Inv is estimated as the book value of assets in December of year $t - 2$ minus the book value of assets in December of year $t - 1$, all over the book value of assets in December of year $t - 2$.

3.2. Factors Formation

Right-hand-side (hereafter RHS) portfolios, commonly used as the explanatory factors in the tested models, are estimated in line with the methodology used by Fama and French (1993, 2015).

The market risk premium (hereafter Mkt) is measured as all sample stocks' monthly value-weighted returns minus the risk-free rate, which is, in our case, the monthly rate equivalent to 13 weeks Treasury's bill rate.

Consistent with Fama and French's (2015) second approach[4], the RHS portfolios are defined, independently, via the size and B/M, size and OP and size and Inv relying to the 2 × 2 structure. Our choice is specifically motivated by the availability of data, as well as the smaller number of firms trading on the Moroccan market. Besides the size factor corresponding to size–B/M sort (hereafter, $SMB_{B/M}$), two others size factors related respectively to size–OP and size–Inv (hereafter SMB_{OP} and SMB_{INV}) are produced.

Regarding the size, stocks are divided into two classes according to whether their market capitalization is lower (S) or higher (B) than the median value of the sample's market capitalization. We take into consideration, from July of year t to June of year t + 1, the capitalization in June of year t for the formulation of portfolios.

Similarly, stocks are divided into two classes according to whether their B/M is lower (L) or higher (H) than the median B/M of the sample. According to Fama and French (1993), we consider July of year t to June of year t + 1 as the study period, and we take into account, for the formation of the portfolios, the book-to-market ratios of the end of the year t − 1 (December).

As the HML factor, we formed profitability and investment factors by replacing B/M with OP and Inv, respectively.

Here, two classes of OP are created based on the median value. The weak portfolio (W) class contains firms whose OP ratios are below the median, while the robust portfolio (R) class contains firms whose OP ratios are above the median. As the B/M ratio, from July of year t to June of the same year, we consider the OP ratio of the end of year t − 1 (December) to form the portfolios.

In sorting stocks related to the investment ratio, two portfolios are formulated. Based on the median value, stocks whose Inv ratios are inferior to the reference value are included in the conservative portfolio (C), while stocks whose Inv ratios are superior to this are listed as aggressive portfolios (A).

Regardless of previous classifications, four portfolios are formed in each sort (e.g., for the size–B/M sort, we have S/L, S/H, B/L and B/H). For each portfolio, we calculate monthly the value-weighted returns from July of year t to June of year t + 1.

The mimic risk factor related to the B/M ratio (hereafter, HML) is estimated, each month, as the mean of the returns on SH and BH (with high book-to-market) portfolios minus the mean returns on the SL and BL (with low book-to-market ratio) portfolios:

$$\mathrm{HML} = \frac{\left(R_{\frac{S}{H}} + R_{\frac{B}{H}}\right)}{2} - \frac{\left(R_{\frac{S}{L}} + R_{\frac{B}{L}}\right)}{2} \tag{1}$$

The mimic risk factor related to the OP ratio (hereafter, RMW) is formed, each month, as the mean of the returns on SR and BR portfolios (profitable companies) minus the mean of the returns on SW and BW portfolios (less profitable companies):

$$\mathrm{RMW} = \frac{\left(R_{\frac{S}{R}} + R_{\frac{B}{R}}\right)}{2} - \frac{\left(R_{\frac{S}{W}} + R_{\frac{B}{W}}\right)}{2} \tag{2}$$

The mimic risk factor related to the Inv ratio (hereafter, CMA) is constituted, each month, as the mean of the returns on SC and BC portfolios (conservative companies) minus the SA and BA portfolios' average returns (companies with an aggressive investment profile):

$$\mathrm{CMA} = \frac{\left(R_{\frac{S}{C}} + R_{\frac{B}{C}}\right)}{2} - \frac{\left(R_{\frac{S}{A}} + R_{\frac{B}{A}}\right)}{2} \tag{3}$$

Monthly, we formed, respectively and independently, $\text{SMB}_{\frac{B}{M}}$, SMB_{OP} and SMB_{INV} as the mean returns on the portfolios (SL and SH; SW and SR; SC and SA) with small companies minus the mean returns on the portfolios (BL and BH; BW and BR; BC and BA) with big companies, as shown in the three distinct equations below:

$$\text{SMB}_{\frac{B}{M}} = \frac{\left(R_{\frac{S}{L}} + R_{\frac{S}{H}}\right)}{2} - \frac{\left(R_{\frac{B}{L}} + R_{\frac{B}{H}}\right)}{2} \tag{4}$$

$$\text{SMB}_{OP} = \frac{\left(R_{\frac{S}{W}} + R_{\frac{S}{R}}\right)}{2} - \frac{\left(R_{\frac{B}{W}} + R_{\frac{B}{R}}\right)}{2} \tag{5}$$

$$\text{SMB}_{INV} = \frac{\left(R_{\frac{S}{C}} + R_{\frac{S}{A}}\right)}{2} - \frac{\left(R_{\frac{B}{C}} + R_{\frac{B}{A}}\right)}{2} \tag{6}$$

Finally, the mimic risk factor related to the size (hereafter SMB) is estimated as the average of $\text{SMB}_{\frac{B}{M}}$, SMB_{OP} and SMB_{INV}, as in the equation below:

$$\text{SMB} = \frac{\left(\text{SMB}_{\frac{B}{M}} + \text{SMB}_{OP} + \text{SMB}_{INV}\right)}{3} \tag{7}$$

3.3. Left-Hand-Side Portfolios Formation

The dependent variables, namely, the left-hand-side portfolios (hereafter LHS), are divided into three double-sorted sets, as below.

Firstly, portfolios are constructed based on size–B/M. Regarding the size sort, stocks are divided into two groups based on the median value (S and B). Independently, we use the 20th and 40th percentiles[5] to form three groups with different B/M ratios: high (H), medium (M), and low (L). The intersection of the two sorts generates six size–B/M portfolios.

Secondly, portfolios are constructed based on size-OP. Similar to the previous classification, we use the median to divide stocks into two classes (S and B) and, independently, we use the 20th and 40th percentiles to structure the three groups of OP ratio: robust (R), medium (M), and weak (W). Then, the intersection of the two classifications generates six size–OP portfolios.

Thirdly, portfolios are constructed based on size–Inv. As was the case in the previous classification, two groups of stocks (S and B) are formed and, independently, we use the 20th and 40th percentiles to structure the three groups of Inv ratio: conservative (C), medium (M), and aggressive (A). Then, the intersection of the two sorts generates six size–Inv portfolios.

For each of the three different sets, the monthly excess returns are defined as the LHS variables.

4. Results and Discussion

4.1. Descriptive Statistics for RHS Factors' Return

The means, t-statistics and standard deviations of the factors' monthly returns are reported in Table 1. The equity premium (average Mkt Return) has the largest significant average return, but with a negative value (-1.77%, $t = -5.27$). From this perspective, Fama and French (2012) found that, in Japan, the equity premium produces an excess return of -0.12% per month, and they argued that those estimates are imprecise[6].

The size premium (average SMB Return) presents a highly significant positive return. This result provides an initial indication regarding the presence of the size effect.

The value premium (average HML Return) holds a positive value, and is significant at the 10% level. The findings show that value stocks (with high B/M) outperform growth ones (with low B/M). The existence of value premium is widely proven in several studies of both developed and emerging markets (Fama and French 1993, 2015, 2017; Novy-Marx 2013 and Cox and Britten 2019).

Table 1. Means, t-statistics and standard deviations of the factor monthly returns.

Factors	Mean (%)	t-Statistic	Standard Deviation (%)
Mkt	−1.77245	**−5.2688** *	4.94413
SMB	0.92233	**2.2008** **	6.15922
HML	0.79783	**1.9919** ***	5.88671
RMW	0.40951	0.9639	6.24408
CMA	0.23419	0.595	5.78424

(*), (**) and (***) respectively indicate 1%, 5% and 10% significance levels.

Profitability premium (average RMW Returns) shows a positive value of 0.41% per month, which means that profitable companies outperform those with weak profitability ratios.

Investment premium (average CMA Returns) presents a weaker but positive value of 0.23% per month, implying companies that invest conservatively outperform those that invest heavily.

Consistent with Foye (2018) and Leite et al. (2018), both RMW and CMA premiums are low and statistically insignificant in emerging Asian markets. These findings show the non-existence of profitability and investment effects on the Moroccan stock exchange. Fama and French (2015) reported that each of the five factors have highly significant positive returns. Except for the Mkt, the results from Table 1 are similar for Morocco in the sense that all premiums are positive.

The correlation between SMB and Mkt in Table 2 is surprising, and it is in contrast with previous results. SMB is correlated negatively with markets, which means that big stocks generally produce higher market betas compared to small stocks. Similar results were found by Mosoeu and Kodongo (2020) for South African market. SMB has a strong positive correlation with profitability, implying that small firms are more connected with robust profitability. Consistent with Ragab et al. (2020) looking at the Egyptian stock market, we find that the correlation between the HML factor and both RMW and CMA factors is weakly negative. However, Fama and French (2015) noticed that CMA and HML have a strongly positive correlation (0.7). RMW has a strong negative correlation with CMA, implying that profitable firms have a tendency to invest aggressively. These results echo those of Alrabadi and Alrabadi (2018) study of Amman stock exchange.

Table 2. Correlations between factors.

	Mkt	SMB	HML	RMW	CMA
Mkt	1				
SMB	−0.312	1			
HML	−0.050	0.115	1		
RMW	0.047	0.382	−0.186	1	
CMA	−0.114	−0.159	−0.182	−0.444	1

Overall, we find that the correlations between factors are mostly below 0.50 (Table 2). This observation excludes any multicollinearity possibility in the estimated model specifications.

4.2. Average Excess Returns for LHS Portfolios

Monthly excess returns are shown in Table 3 for portfolios composed of two classes, independently, on the basis of size and either B/M, OP or Inv for the entire 18-year period.

Table 3. Monthly excess return values for LHS portfolios.

Sort A: Size–B/M			
	Low	Medium	High
Small	−0.017 (−3.2625)	−0.004 (−0.6292)	−0.011 (−2.5646)
Standard deviation	7.705%	10.141%	6.458%
Big	−0.019 (−5.4056)	−0.019 (−5.0198)	−0.006 (−0.9878)
Standard deviation	5.216%	5.615%	9.00%
Sort B: Size–OP			
	Weak	Medium	Robust
Small	−0.011 (−2.5193)	−0.009 (−1.4973)	−0.003 (−0.4503)
Standard deviation	6.724%	9.014%	10.971%
Big	−0.016 (−2.6514)	−0.019 (−4.8500)	−0.017 (−4.8422)
Standard deviation	9.107%	6.013%	5.267%
Sort C: Size–INV			
	Conservative	Medium	Aggressive
Small	−0.003 (−0.5916)	−0.018 (−3.6919)	−0.005 (−0.6534)
Standard deviation	7.686%	7.283%	10.861%
Big	−0.017 (−5.0468)	−0.021 (−3.9738)	−0.011 (−1.9411)
Standard deviation	5.051%	7.661%	8.329%

t-statistics are shown in parentheses.

In sort A, high-B/M portfolios show greater returns than ones with low B/M across both size groups. When holding B/M constant, the average return generally falls as the size increases, except for small portfolios with high B/M. The size effect is unclear, which is consistent with the results reported in Table 2.

In the size–profitability sort (sort B), average to small capitalization leads to greater returns. Specifically, across all profitability groups, small portfolios outperform big portfolios, which is in accordance with the size effect preliminarily documented in Table 1. Furthermore, across both size groups, robust profitability portfolios yield the greatest returns with the exception of big capitalization portfolios with weak profitability. This result is in line with the insignificantly low average RMW returns shown in Table 1.

Finally, an interesting observation shows that big capitalization companies with an aggressive investment profile outperform those that invest less (sort C). These results are consistent with Cox and Britten's (2019) for the Johannesburg stock market. The authors argue that smaller firms do not employ potential funding for their investments, while in contrast, large companies may do. The investment pattern in average returns confirms the insignificantly low average CMA returns shown in Table 1. Regarding the size effect, the results seen for sort C are identical to those reported for sort B. The small portfolios follow a similar pattern to the size–OP sorts: small stocks outperform big stocks across all investment groups.

Despite the highly significant positive returns of the size premium, as shown in Table 1, the results of average returns in Table 3 (sort A) show little evidence of a size effect. However, the value effect is clearly shown in the results obtained in both Tables 1 and 3. Therefore, the value effect is more pronounced than the size effect.

4.3. Factor Spanning Tests

Table 4 shows the regressions, and for each factor, the returns are explained by the four others. The intercept in MKT regressions is clearly significant at the 1% level. Therefore, the market factor Mkt is obviously not redundant. Using Fama and French's dataset, Racicot and Rentz (2017) conclude that the Mkt factor is the only persistently significant factor.

Table 4. Factor spanning tests.

	Coefficient						t-Statistic						
	Int	**Mkt**	**SMB**	**HML**	**RMW**	**CMA**	**Int**	**Mkt**	**SMB**	**HML**	**RMW**	**CMA**	**Adjusted R^2**
Mkt	−0.015		−0.309	0.001	0.115	−0.095	**−4.680 ***		−5.429	0.012	1.774	−1.478	0.123
SMB	−0.001	−0.397		0.199	0.444	0.041	−0.341	−5.429		3.056	6.603	0.564	0.273
HML	0.008	0.001	0.213		−0.395	−0.338	**2.141 ****	0.012	3.056		−5.540	−4.706	0.148
RMW	0.006	0.128	0.386	−0.321		−0.461	**1.810 *****	1.774	6.603	−5.540		−7.647	0.385
CMA	0.004	−0.108	0.037	−0.281	−0.471		1.176	−1.478	0.564	−4.706	−7.647		0.268

(*), (**) and (***) respectively indicate 1%, 5% and 10% significance levels.

For the period 2002–2020, we can see that the value factor is useful in explaining the variation in Moroccan stock returns, since its regression intercept is positive and greater than two standard errors.

Regarding the factor spanning test, the profitability factor is also important in describing the Moroccan returns. We note that the RMW intercept is positive and statistically significant at 10%.

The SMB factor seems more redundant than the CMA factor. Both intercepts for SMB and CMA regressions are insignificant (t = −0.341, t = 1.176, respectively).

In Morocco, the most powerful factor is Mkt, with possible assistance from HML and RMW.

4.4. Summary Asset Pricing Tests (GRS)

Proposed by Gibbons et al. (1989), the GRS statistic and its *p*-value (p(GRS)) assess whether all intercept estimates in the time series regression are indistinguishable from zero. Consistently with Fama and French (2017), we augment our empirical analysis by adding other summary metrics: (1) $A\,|\,a_i\,|$, the intercepts' mean absolute value; (2) $Aa_i^2\,/\,A\bar{r}_i^2$, the mean squared intercept divided by the mean squared $\bar{r}_i$—this value corresponds to the difference between portfolio i's mean return and the market portfolio's mean value-weighted return; (3) $As^2(a_i)\,/\,Aa_i^2$, the mean of the squared sample standard errors of the intercept values divided by Aa_i^2, and (4) AR^2, the mean adjusted R^2.

The table below outlines a summary of the results for the CAPM model, the three-factor model of Fama and French (1993) and the five-factor model of Fama and French (2015), and we also use a three-factor model (hereafter 3FM) including the MKT, HML and RMW as the explanatory factors. The latter model verifies the factor spanning observations in such a manner that it drops redundant factors (SMB, CMA) when describing Moroccan average returns. Several studies support the role of the profitability factor in emerging markets (Lin 2017; Guo et al. 2017 and Cox and Britten 2019).

The results highlight that the GRS test generally rejects all models considered for the three sets of LHS portfolios. We observe that the probability (*p*-value) for all models is close to zero, except for in the results for the size–OP sort, where this model performs better, but the p-values are still less than 0.24. However, the main purpose of our tests is to analyze the performances of competing models, rather than assessing whether they are rejected or not; this is why, initially, we added other statistics to the GRS test.

When employing the six size–B/M portfolios as the main test assets, the estimates of $Aa_i^2\,/\,A\bar{r}_i^2$ for the FF5F model yield 0.49. Consequently, in units of return squared, the model fails to explain around half the variation in returns, which is the lowest value when compared to other models (the values of the ratio for CAPM, the FF3F model and the 3FM are, respectively, 0.86, 0.56 and 0.56). Table 5 also highlights for the five-factor model the smaller value of Aa_i. The results imply that adding CMA and RMW to the FF3F model significantly increases the average R^2, which increases from 55% to 66%. Despite this success, the biggest improvement in the estimate of $As^2(a_i)/Aa_i^2$ is produced by the 3FM, since the sampling error reached 52% in terms of the level of unexplained average returns. We can suppose that the 3FM is more reliable, since it generates lower GRS estimates.

Table 5. Comparison of model performance using the GRS test and other metrics.

Model Factors	GRS	p(GRS)	$A\mid a_i\mid$	$Aa_i^2/A\bar{r}_i^2$	$As^2(a_i)/Aa_i^2$	AR^2
			Sort A: 2 × 3 size-B/M			
Mkt	2.86	0.01	0.0064	0.86	0.45	0.29
Mkt SMB HML	4.26	0.00	0.0048	0.56	0.44	0.55
Mkt SMB HML RMW CMA	3.73	0.00	0.0043	0.49	0.43	0.60
Mkt HML RMW	2.97	0.01	0.0049	0.56	0.52	0.46
			Sort B: 2 × 3 size-OP			
Mkt	1.58	0.15	0.0046	0.68	0.73	0.30
Mkt SMB HML	1.67	0.13	0.0046	0.65	0.59	0.50
Mkt SMB HML RMW CMA	1.47	0.19	0.0038	0.51	0.47	0.63
Mkt HML RMW	1.33	0.24	0.0035	0.47	0.79	0.45
			Sort C: 2 × 3 size-Inv			
Mkt	2.38	0.03	0.0069	0.74	0.47	0.31
Mkt SMB HML	2.04	0.06	0.0056	0.57	0.39	0.49
Mkt SMB HML RMW CMA	2.41	0.03	0.0054	0.51	0.32	0.62
Mkt HML RMW	1.92	0.08	0.0057	0.53	0.53	0.40

The asset pricing tests applied to sort B confirm that the 3FM reduces redundant factors compared to the competing models. According to GRS test, the model still produces a higher, yet incomplete, description of the Moroccan average return in comparison with the FF5F and FF3F models. In addition, the estimates of $Aa_i^2/A\bar{r}_i^2$ and Aa_i for the model present the lowest and highest values for the $As^2(a_i)/Aa_i^2$ estimate. These results suggest that the 3FM performs very well.

For the Moroccan size–inv portfolios, the FF5F model leaves the lowest proportion of variation on returns unexplained ($\frac{Aa_i^2}{A\bar{r}_i^2}$ = 51%). The results also show that the FF5F model generates the smallest dispersion of the intercepts. However, this is bad news[7] for the five-factor model; $As^2(a_i)/Aa_i^2$ suggests that just 32% of the variation in average returns is unexplained, reflecting random irregularities in the sample data. In contrast, the three-factor model seems to keep its relative position in terms of explaining Moroccan stock return. The model yields slightly lower GRS test results than the other models, and the sampling error regarding the dispersion of the intercepts is 53%.

Overall, the CAPM appears to be the worst-performing model, followed by the FF3F model, in terms of the magnitude of all summary metrics. The results are a bit ambiguous in the comparison of the FF5F model and the 3FM, since not all performance metrics show improvements for one rather than the other. The 3FM model is the more effective asset pricing model when looking at the estimates of GRS test and the ratios of $As^2(a_i)/Aa_i^2$ in all sorts of portfolios. Yet the point estimate of the average R^2 for the FF5F model tells a different story. The results reveal that the average R^2 of the five-factor model ranges from 60% to 63% (the highest value) for different sets of LHS portfolios.

To sum up, both models have difficulties that prevent them from explaining all Moroccan stock returns.

4.5. Asset Pricing Details

Tables 6–8 detail the findings of time series regressions of the three competing models—the CAPM, FF3F model and FF5F model—for the three different sets of portfolios. Our focus tends towards the three most important points that should be highlighted. First, the only case where a financial asset valuation model is precisely defined is when the times-series regressions' intercepts are indistinguishable from zero. Second, significant slopes of the risk factors confirm their capability in explaining stock returns. Third, with the highest average R^2, the winner is the model that captures the variation in stock returns.

4.5.1. Size–B/M Sorts

In comparing the number of statistically significant intercepts produced by each of our factor models, we notice that the three can capture the same variation in the size–B/M portfolios, and we cannot identify any differences between them. At the 5% level of confidence, five out of the six portfolios' intercepts are insignificant. However, regarding the average R^2, the CAPM performs poorly, as it leaves around 70% of the average returns unexplained.

The FF5F model has a relatively greater explanatory power than the FF3F model, since its average R^2 increased from 55% to 60%. These results imply that the FF5F model outperforms the two other competing models. Regardless of the model tested, the regression findings prove the best ability of the market factor in explaining the six double-sorted portfolios' returns. At the 5% level, all of the market slopes are statistically significant. Similar results are shown for both FF3F and FF5F models. The SMB and HML factors' coefficients deserve emphasis. Consistently with Fama and French (1993, 2015), the SMB slopes show a positive value for all small portfolios, and they are negative for big ones. In addition, portfolios with low B/M stocks produce negative slopes, and those with high B/M stocks produce positive ones. Therefore, the slopes on SMB for stocks are related to size, and the slopes on HML are intuitively related to book-to-market ratios. Statistically, four out of six SMB factor coefficients are significant at 5%, while five out of six HML factor coefficients are significant at the same level. These results confirm that the HML factor is more important than the SMB factor derived via spanning tests.

In contrast, the RMW factor does show the same pattern as in the spanning test. Only one out six OP coefficients is significant at 5%, which means that the role held by the profitability factor in describing the size–B/M portfolios' average returns is not robust. These results are in line with Ragab et al. (2020) study of the Egyptian stock market.

As to the CMA coefficients, our results echo those delivered by Fama and French (2015) that growth stocks invest aggressively compared to value stocks. However, at the 5% level of confidence, only two out six of the slopes are significant.

4.5.2. Size–OP Sorts

Table 7 shows the regression analysis of the six portfolios classed on the basis of size and profitability ratio. Indeed, the interpretation of regression intercepts and the coefficient of market factor are similar to those highlighted in Table 6. The FF5F model still outperforms the competing models in terms of the average R^2. Related to the SMB factor, the FF5F regressions show more significant SMB slopes than those provided by FF3F regression. Five out six SMB slopes are significant at the 5% level, while three out of six coefficients are significant in the FF3F model. These results are concordant with those reported by Erdinç (2018) for the Turkey stock market.

Adding RMW and CMA to the FF3F model reduces the role played by the HML factor in explaining the average returns of size–op portfolios. Four out of six of the HML coefficients have shown statistical significance in the FF3F regression results, while only two out of six are significant at the 5% level of confidence in the FF5F regression slopes.

The RMW slopes for the size–op portfolios provide predictable signs that the portfolios are sorted on profitability. Although the OP coefficient is positive for high-profitability portfolios and negative for low-profitability ones, five out six slopes are statistically significant at the 5% level. Fama and French (2015) reveal that companies with weak profitability invest less. However, this pattern is confirmed only for small portfolios (SW portfolios have a positive coefficient) and the reverse is true for big portfolios (BW ones have a negative coefficient).

4.5.3. Size–Investment Sorts

The regression intercepts of the six portfolios based on size and investment ratio show different results compared to those of portfolios based on the two other sorts. Regarding the CAPM and FF3F models, five out of six of the portfolios have insignificant intercepts. However, for FF5F, four out of six portfolios have insignificant intercepts at the 5% level. This, in turn, shows that the FF5F achieves a lower improvement in the explanatory power of stock returns compared to the competing models. However, the average R^2 value seems to suggest otherwise. The FF5F model effectively describes the size–investment portfolios' average returns, but it is still insufficient (62% for FF5F, contrary to 49% for FF3F and 30.7% for CAPM). Table 8 shows that the market factor maintains its role in capturing the variation in returns, and in the case of the size–investment sort, at the 5% level of confidence, all the coefficients are significant statistically. The FF3F regression results emphasize the improvements of the SMB factor over the HML factor. Four out of six of the SMB coefficients are significant at the 5% level. However, two out of six of the HML coefficients are significant at the same confidence level. The SMB factor plays the same role even after including CMA and RMW factors in the FF3F equation model. In contrast, the number of HML coefficients with significant values increased to four out of six in the FF5F model, rather than two out six coefficients in the case of the FF3F model. Consistently with Ragab et al. (2020), most of the RMW slopes are negative, and only four out of six are significant at the 5% level. In addition, the coefficients of the CMA factor follow the same pattern as indicated in Fama and French (2015) findings. Although these results prove that, in each group of size, conservative portfolios load positively and those with an aggressive investment profile load negatively, only four out of six slopes are significant.

Table 6. Regression results of the CAPM, FF3F model and FF5F model for the 6 value-weighted size–B/M portfolios (July 2002–June 2020).

Dependent Variables		**CAPM**			**FF3F Model**					**FF5F Model**						
		Alpha	**Rm-Rf**	**R^2**	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**R^2**	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**RMW**	**CMA**	**R^2**
SL	Coeff.	−0.01	0.416	0.067	−0.008	0.649	0.678	−0.505	0.435	−0.008	0.613	0.640	−0.522	0.025	−0.139	0.442
	t-stat	−1.808	**4.054 ***		−1.857	**7.718 ***	**9.987 ***	**−7.477 ***		−1.836	**7.167 ***	**8.482 ***	**−7.157 ***	0.307	−1.739	
SMHL	Coeff.	0.007	0.621	0.087	0.001	1.074	1.094	0.475	0.597	0.000	0.967	0.959	0.459	0.156	−0.330	0.648
	t-stat	0.951	**4.644 ***		0.172	**11.485 ***	**14.500 ***	**6.325 ***		0.097	**10.812 ***	**12.159 ***	**6.016 ***	1.844	**−3.936 ***	
SH	Coeff.	−0.003	0.458	0.119	−0.007	0.666	0.48	0.371	0.449	−0.005	0.822	0.739	0.301	−0.452	0.247	0.718
	t-stat	−0.719	**5.476 ***		−1.962	**9.576 ***	**8.545 ***	**6.633 ***		−1.844	**16.128 ***	**16.425 ***	**6.930 ***	**−9.367 ***	**5.184 ***	
BL	Coeff.	−0.001	1.036	0.965	0.000	1.027	−0.008	−0.099	0.977	0.000	1.025	−0.011	−0.099	0.003	−0.007	0.977
	t-stat	−1.153	**76.825 ***		−0.201	**90.117 ***	−0.878	**−10.765 ***		−0.21	**87.569 ***	−1.049	**−9.924 ***	0.275	−0.648	
BMHL	Coeff.	−0.008	0.616	0.291	−0.009	0.599	−0.057	0.080	0.294	−0.009	0.618	−0.039	0.091	−0.009	0.078	0.294
	t-stat	**−2.415 ***	**9.454 ***		**−2.526 ***	**8.747 ***	−1.037	1.452		**5.551 ****	**8.810 ***	−0.623	1.515	−0.137	1.189	
BH	Coeff.	0.010	0.891	0.236	0.004	0.844	−0.252	0.844	0.545	0.004	0.869	−0.228	0.859	−0.01	0.107	0.545
	t-stat	1.713	**8.210 ***		1.018	**9.571 ***	**−3.540 ***	**11.913 ***		0.985	**9.631 ***	**−2.859 ****	**11.171 ***	−0.113	1.267	
Average Adjusted R^2				0.294					0.550							0.604

(*) and (**) respectively indicate 1% and 5% significance levels.

Table 7. Regression results of the CAPM, FF3F model and FF5F model for the 6 value-weighted size–OP portfolios (July 2002–June 2020).

Dependent Variables		**CAPM**			**FF3F Model**					**FF5F Model**						
		Alpha	**Rm-Rf**	**R^2**	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**R^2**	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**RMW**	**CMA**	**R^2**
SW	Coeff.	−0.003	0.509	0.136	−0.006	0.76	0.603	0.283	0.497	−0.002	0.936	0.938	0.139	−0.666	0.114	0.852
	t-stat	−0.555	**5.902 ***		−1.695	**10.978 ***	−1.695	**5.094 ***		−1.181	**24.364 ***	**27.696 ***	4.243	**−18.342 ***	**3.174 ***	
SMRW	Coeff.	−0.001	0.479	0.065	−0.001	0.725	0.657	−0.142	0.241	−0.001	0.803	0.747	−0.116	−0.080	0.277	0.274
	t-stat	−0.111	**3.980 ***		−0.220	**6.360 ***	**7.143 ***	−1.553		−0.218	**7.032 ***	**7.412 ***	−1.192	−0.744	**2.595 ****	
SR	Coeff.	0.009	0.708	0.098	0.005	1.255	1.391	0.108	0.660	0.002	1.047	0.002	0.211	0.626	−0.305	0.828
	t-stat	1.221	**4.929 ***		1.115	**13.522 ***	**18.575 ***	1.446		0.621	**15.458 ***	**17.407 ***	3.649	**9.770 ***	**−4.811 ***	
BW	Coeff.	0.004	1.149	0.386	0.002	1.033	−0.349	0.33	0.467	0.007	1.115	−0.073	0.081	−0.743	−0.406	0.624
	t-stat	0.762	**11.672 ***		0.510	**10.705 ***	**−4.474 ***	**4.254 ***		1.796	**13.428 ***	−1.003	1.140	**−9.465 ***	**−5.222 ***	
BMRW	Coeff.	−0.011	0.524	0.182	−0.012	0.556	0.058	0.161	0.204	−0.010	0.613	0.189	0.081	−0.295	−0.047	0.261
	t-stat	**−2.685 ****	**6.979 ***		**−3.025 ***	**7.139 ***	0.930	**2.568 ****		**−2.650 ****	**7.977 ***	**2.784 ****	1.231	**−4.057 ***	−0.655	
BR	Coeff.	0.001	1.015	0.907	0.001	1.002	−0.022	−0.064	0.912	0.000	0.979	−0.092	−0.005	0.181	0.086	0.940
	t-stat	0.546	**45.802 ***		0.994	**44.262 ***	−1.211	**−3.518 ***		−0.047	**51.069 ***	**−5.423 ***	−0.334	**9.996 ***	**4.765 ***	
Average Adjusted R^2				0.295					0.497							0.630

(*) and (**) respectively indicate 1% and 5% significance levels.

Table 8. Regression results of the CAPM, FF3F model and FF5F model for the 6 value-weighted size–Inv portfolios (July 2002–June 2020).

Dependent Variables		**CAPM**			**FF3F Model**					**FF5F Model**						
		Alpha	**Rm-Rf**	**R^2**	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**R^2**	**Alpha**	**Rm-Rf**	**SMB**	**HML**	**RMW**	**CMA**	**R^2**
SC	Coeff.	0.007	0.579	0.135	0.005	0.848	0.673	0.131	0.414	0.005	1.05	0.894	0.214	−0.173	0.753	0.790
	t-stat	1.388	**5.875 ***		1.095	**9.931 ***	**9.757 ***	1.914		1.744	**20.034 ***	**19.340 ***	**4.781 ***	**−3.492 ***	**15.362 ***	
SMCA	Coeff.	−0.009	0.503	0.112	−0.011	0.672	0.415	0.137	0.237	−0.009	0.781	0.629	0.039	−0.435	0.049	0.352
	t-stat	−1.892	**5.309 ***		**−2.443 ****	**7.275 ***	**5.570 ***	1.847		**−2.068 ****	**8.966 ***	**8.187 ***	0.521	**−5.276 ***	0.599	
SA	Coeff.	0.008	0.716	0.102	0.002	1.259	1.33	0.459	0.715	0.002	1.056	1.107	0.376	0.174	−0.760	0.906
	t-stat	1.056	**5.042 ***		0.371	**14.958 ***	**19.570 ***	**6.790 ***		0.717	**21.379 ***	**25.401 ***	**8.936 ***	**3.730 ***	**−16.434 ***	
BC	Coeff.	−0.003	0.830	0.659	−0.003	0.835	0.008	0.031	0.657	−0.004	0.858	−0.006	0.101	0.125	0.238	0.709
	t-stat	−1.232	**20.406 ***		−1.328	**19.455 ***	0.237	0.887		−1.974	**21.183 ***	−0.182	**2.914 ***	**3.261 ***	**6.290 ***	
BMCA	Coeff.	−0.004	0.924	0.353	−0.005	0.923	−0.017	0.099	0.352	−0.004	0.942	0.034	0.059	−0.129	−0.050	0.353
	t-stat	−0.973	**10.868 ***		−1.11	**10.316 ***	−0.238	1.379		−0.921	**10.283 ***	0.427	0.758	−1.493	−0.582	
BA	Coeff.	0.010	1.170	0.480	0.008	1.088	−0.266	0.350	0.562	0.009	1.033	−0.280	0.258	−0.119	−0.382	0.612
	t-stat	**2.242 ****	**14.121 ***		1.98	**13.600 ***	**−4.113 ***	**5.446 ***		**2.419 ****	**13.381 ***	**−4.118 ***	**3.919 ***	−1.626	**−5.285 ***	
Average Adjusted R^2				0.307					0.490							0.620

(*) and (**) respectively indicate 1% and 5% significance levels.

5. Conclusions

This study offers new evidence on the usefulness of asset pricing models in an emerging market. As such, this paper extends the current literature into African emerging markets by evaluating and comparing, for the first time, the explanatory power of the CAPM, FF3F model and FF5F model in a sample taken from the Moroccan stock exchange.

Applying time series regression and the GRS test, the one-factor model proves to be the worst-performing model in explaining variation in Moroccan stock returns. However, taking into account the findings regarding the t-statistics of the slopes of the market factor, they were strongly significant under the three models, and all sets confounded. In comparing between the three- and five-factor models, the results seem to generally confirm the superiority of the FF5F model. Consistently with Fama and French (2015), the GRS test typically rejects, for the three sets of dependent variables, all the models considered. Therefore, the standard models fail to completely explain the Moroccan returns. The results show the existence of value and size effects in the market. However, on the basis of our analysis, we conclude that the value effect is more pronounced than the size effect. The vast majority of studies on emerging markets conclude on the preeminence of the value effect over the size effect (Fama and French 2012; Barry et al. 2002; Eraslan 2013). For their part, the profitability and investment effects are almost absent. Foye (2018) and Leite et al. (2018) found similar results in the emerging Asian market.

Inconsistent with Fama and French (2015), the value factor was not redundant; it still operates as an explanatory variable when including investment and profitability factors. Ryan et al. (2021), while investigating value factor redundancy in the Vietnamese stock market, found that the value factor remains important after the inclusion of profitability and investment factors. Otherwise, both the investment and size factors are the redundant factors. From this perspective, we have analyzed the performance of a model that drops redundant factors when describing Moroccan average returns, in order to confirm the results of the factor spanning tests. This includes the three explanatory returns of Mkt, HML and RMW. The results do not show the preeminence of this model over the FF5F model. On one hand, in terms of the estimates of the GRS test and the ratio of $As^2(a_i)/Aa_i^2$, 3FM is the best-performing financial asset valuation model. On the other hand, the FF5F model outperforms the competing models in terms of the estimate of the average R^2.

In summing up, the results confirm the challenge that asset pricing models face when applied in emerging markets. We conclude that all tested models fail to completely explain the Moroccan stock returns. Similar results were observed by Alrabadi and Alrabadi (2018) for Amman's market, Ragab et al. (2020) for Egyptian markets and Foye and Valentinčič (2020) for Indonesian markets. This study suggests we lean towards other appropriate risk factors in the explanation of stock returns. Future studies could explore different directions to improve the addressing of this challenge. First, asset pricing models could be developed by considering more suitable risk factors as a response to the specific characteristics of given emerging markets (Zaremba and Czapkiewicz 2017; Alrabadi and Alrabadi 2018; Mosoeu and Kodongo 2020; Ali 2022). Second, the application and comparison of various sorts of LHS and RHS portfolios, as well as other statistical metrics and methods, could be explored (Dimson 1979; Mosoeu and Kodongo 2020; Ali and Ülkü 2021; Hansen 2022).

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Notes

[1] M. M. Carhart (1997) proposed the Carhart Four Factor Model by introducing into the FF3F model a momentum-mimicking risk factor.

[2] In North Africa, Morocco takes the lead in terms of the equity of market capitalization in the Maghreb (USD 65.6, 57.1% of GDP), followed by Egypt (USD 41.4 billion, 11.3% of GDP) and Tunisia (USD 8.5 billion, 20.6% of GDP). In sub-Saharan Africa, South Africa has the highest market capitalization (USD 1 trillion, 313.5% of GDP), followed by Nigeria (USD 56 billion, 12% of GDP), Kenya (USD 21.4 billion, 13.1% of GDP) and Ghana (USD 9.2 billion, 13.5% of GDP). EIB, La finance en Afrique, naviguer en eaux troubles, 2022.

[3] Available on the Moroccan stock exchange website: www.casablanca-bourse.com (Accessed on 4 April 2022).

[4] Fama and French (2015) employed three separate methods—2×3, 2×2 and $2 \times 2 \times 2 \times 2$—to contrast the five factors. The authors argue that the choice of any sort is arbitrary, as the results are similar.

[5] Due to the small sample of our study, it was difficult to form effectively diversified portfolios. The 20th and 40th percentiles are the best combinations. For their part, Cox and Britten (2019) used the 33rd and 66th percentiles for the Johannesburg stock exchange.

[6] Fama and French (2017) revealed that, for Japan, the average Mkt Return is near zero (0.01% per month). Negative average value is also found by several authors in different markets' stock exchanges, such as the Nairobi stock market (Achola and Muriu 2016), Amman's stock market (Alrabadi and Alrabadi 2018) and the Polish stock market (Zaremba et al. 2019).

[7] According to Fama and French (2017), a low value of $\text{Aai}^2/\text{Ari}^2$ bodes well for an asset pricing model. In contrast, a low value of $\text{As}^2(\text{ai})/\ \text{Aai}^2$ is less favorable.

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