International Journal of Economics and Financial Issues

ISSN: 2146-4138

available at http: www.econjournals.com

International Journal of Economics and Financial Issues, 2024, 14(6), 182-194.

Cross-Sectionnal Patterns in Moroccan Sock Returns: A Fama-French Perspective

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Received: 15 July 2024 **Accepted:** 25 September 2024 **DOI:** https://doi.org/10.32479/ijefi.17032

ABSTRACT

Drawing on the Fama and French models, we examine the role of market factor (beta), fundamental characteristics (size, book-to-market, profitability and investment) and the momentum in explaining cross-sectional stock returns in the Moroccan market. The sample consists of non-financial stocks over the period from July 2008 to June 2020. In this research and for the first time, we contribute to the current body of asset pricing literature by embracing three different empirical methodologies. First, we use an adaptation of cross-sectional methodologies from Fama and MacBeth (1973) and Fama and French (1992). Second, we opt for portfolios as dependent variables to reduce potential estimation errors associated with individual stocks. Third, we specifically adjust for the errors-in-variables issue using the methodology proposed by Brennan et al. (1998). Our results indicate that beta coefficients are statistically insignificant in both first and second methodologies. Furthermore, none of the characteristic's variables meet the criteria for a good explanatory variable, as they fail to consistently exhibit a significant level of significance in all cases. Generally, the momentum factor emerges as the most promising variable. We conclude that the tested models are incomplete in explaining variations in Moroccan stock returns. Even after adjusting for model risk, some effects persist.

Keywords: Beta, Size, Book-to-market, Profitability, Investment, Momentum
JEL Classifications: G11, G12

1. INTRODUCTION

For many years until now, financial literature has aimed to explore and understand the risk-return relationship. This path of investigation started with the development of the one-factor model, referred as the CAPM (Sharpe, 1964). The power of this model lies in its simple implication that stock returns are described by the systematic singular factor known as beta (β). Although, it is arguably the advances of Roll in 1977 that the model has demonstrated noticeable empirical limitations. The author states that return generating process is a function of many factors (Zada et al., 2017). Since that, several are debates over which factors doing better job in explaining variation in stock returns. In spite of its drawbacks, the CAPM remains a pivotal reference point for all subsequent models used in the valuation of financial assets. Fama and French (FF, 1992, 1993) included the size (MC) and the book-to-market (B/M) factors, besides β, to form the three-factor (FF3F) model. They found that the latter explain better the stock returns than the CAPM. Despite its empirical success, several studies have characterized the FF3F model as insufficient and have suggested the role of potential new factors in describing variations in stock returns (e.g., Titman et al., 2004; Novy-Marx, 2013). In response to these conclusions, FF (2006, 2015) proposed a new asset pricing equation by incorporating to their FF3F model: the profitability (OP) and the investment (Inv) factors. Known as the FF five-factor (FF5F) model, it exhibited substantial progress when compared to the FF3F model in pricing stock returns in international level (FF, 2017). To further enhance the model, the authors developed a six-factor model (FF6F) three years later by incorporating the momentum (Mom) factor.

In the wake of the FF developments, plenty of studies tried to examine the role of β, MC, B/M, OP, Inv and Mom factors in describing average returns, apart from the US market, initially in developed markets and subsequently in emerging markets, with a specific focus on Asian markets (e.g., China, India). Nevertheless, the performance of factors and financial asset valuation models can vary when examined in different markets and countries (Ali, 2022). Considering the interconnectivity of developed stock markets, findings frequently exhibit similarities (e.g., Walkshäusl and Lobe, 2014; Fama and French, 2017). For their part, emerging markets possess distinctive features that may pose challenges to standard asset pricing models (Jiao, 2018; Foye, 2018; Mosoeu and Kodongo, 2020). This divergence in results motivate us to analyze the assigned role of each of the above-cited factors in explaining stock returns, especially for emerging market.

Only a handful of studies have delved into emerging markets in Africa, with a notable gap, particularly in the case of North African markets. Our investigation places particular emphasis on the Moroccan market. Including asset pricing models, the existing literature on the explanatory role of each factor is limited in this market. Our paper provides an out of sample examination of the Fama and French (1992, 1993, 2006, 2015) factors. As Campbell et al. (1997) specified, the use of different study periods, various data sources, and diverse markets can contribute to out-of-sample validation of the true performance of multifactor asset pricing model (Alaoui Taïb, 2014). The existing study that closely resembles ours is the one conducted by Alaoui Taïb and Benfeddoul (2023a). The authors compared the performance of FF3F and FF5F models in explaining the Moroccan stock market using time series regressions. Nevertheless, our study provides a more microscopic approach to this debate by focusing in the role attributed to each factor, included in the models tested, in describing the variation in Moroccan stock returns. In addition, we considered the latest FF6F model in our comparative analysis.

Our objective is to examine the role of each factor (β, MC, B/M, OP, Inv, and Mom) in explaining stock returns in the Moroccan stock market and assess its robustness in the presence or absence of other possible competing variables. In this research and for the first time, we contribute to the current body of asset pricing literature by embracing three different empirical methodologies. First, we use an adaptation of cross-sectional methodologies from Fama and MacBeth (FM, 1973) and FF (1992) by regressing the monthly excess returns of individual stocks on their estimated post-β and on variables from FF3F, FF5F, and FF6F models. In the second methodology, we replace the calculated values of the explanatory variables with their estimated coefficients. We opt for portfolios instead of individual stocks to reduce potential estimation errors associated with individual values. Third, we specifically adjust for the errors-in-variables issue using the methodology proposed by Brennan et al. (1998). We calculate the risk-adjusted (R_d) individual stocks returns, which are subsequently utilized as the dependent variable in cross-sectional regression. Our sample consists of the entire set of monthly return data for each company and their available annual accounting data, requiring selection criteria over the study period from July 2008 to June 2020.

The key findings of the paper are as follows: the β factor shows non-significant coefficients among both the first and the second methodologies. There is limited evidence to substantiate the crucial role of the tested characteristics in explaining the variation in the Moroccan stock returns. A good explanatory variable should exhibit a consistent level of significance in all cases. None of the variables satisfy this evidence, except for the Mom factor. Furthermore, even after adjusting for model risk, some effects persist. This suggests that the risk adjustment using the asset pricing errors from all the competing models appears incomplete, leading to the rejection of the models.

The remainder of the paper is organized as follows: Initially, we provide a concise literature review. Next, we detail the data and methodologies employed in the study. Ultimately, we synthesize and discuss the outcomes of the cross-sectional regression analysis.

2. LITERATURE REVIEW

With the rise of extensive literature on stock market anomalies, it has become evident that the explanatory power of the single market factor in the CAPM is no longer sufficient. As a result, many researchers have attempted to develop more pertinent multifactor models. FF (1992, 1993) advanced a new model addressing the two widely recognized anomalies presented by Banz (1981) and Stattman (1980). The authors included, besides the β, two further factors, the MC and the B/M, respectively. The substantial importance of the two additional factors in pricing the variation in stock returns has been confirmed in many studies (from developed markets: e.g., Fama and French, 2008; Bhatnagar and Ramlogan, 2012; and in emerging markets: e.g., Xie and Qu, 2016; Shah et al., 2021). In spite of its acclaim among both practitioners and academics, several studies indicated that the FF3F model may have limitations. Titman et al. (2004) and Novy-Marx (2013) stressed the important role of the Inv and OP factors in pricing the average stock returns, respectively. Therefore, in order to account for OP and Inv patterns, Fama and French (2015) extended the FF3F model and introduced the OP and Inv factors. From an international sample of 23 developed markets, FF (2017) evaluated the performance of both their models. Despite a few exceptions, the findings underscored the predominance of the FF5F model over its previous in pricing returns within these regions. Similar results are concluded by Chai et al. (2019) in describing large Australian stocks. Regarding emerging markets, Lin (2017) validated the resilience of the model in pricing the Chinese market returns (Zhang et al., 2022). In the latest iteration, FF (2018) added to their five-factor model a sixth factor related to the momentum variable due to, as they advanced, its popular demand. They concluded that this six-model performs well in all tests.

Nichol and Dowling (2014) compared, in the UK market, the FF3F, FF5F and Chen et al. (2011)[1] models and concluded that all models ultimately fail the full set of FM tests. They found that, in each FF3F and FF5F models, only β and B/M factors are significant while the FF5F's OP factor approaches significance at

1 Chen et al. (2011) developed a three-factor model which add to the β, OP and Inv factors.

just above 10%. Furthermore, the MC and the Inv factors appeared not to be effective in the UK context. In the US market, Kim and Skoulakis (2018) proposed a modification of the two-pass cross-sectional regression (FM) by using the regression calibration approach and compared the implication of CAPM, FF3F and FF5F models. The author formally rejected the null hypothesis of correct model specification, for all the compared models. Kubota and Takehara (2018) found that, in Japan, neither the OP factor nor the Inv factor was statistically significant which is coherent with Fama and French (2017) conclusions regarding the same market. Using time-series regressions and the FM (1973) methodology, the findings of Chakroun and Hmaied (2019) showed some marginal improvement of the FF5F over the FF3F in capturing the variation in French stock returns regarding the R^2. However, the second stage FM (1973) regression on the 25 (5×5) sorts on MC-B/M, MC-OP and MC-Inv groups showed negatively significant intercepts. For their part, the Inv risk premium seems to be better priced in the market than the OP factor as the latter is not significant in any case. In the same perspective of model comparison, Fletcher (2019) found that the FF6F model with small spread factors provides the best performance among the set of models considered in the U.K stock market. In order to provide an updated view on the drivers of German stock returns, O'Connell (2023) evaluated the relative performance of nine competing neoclassical asset pricing models. The author found that the FF6F model, with both traditional and updated value factors, emerges as the dominant model.

Differently from the FF (2006, 2015) definitions of variables, Guo et al. (2017) suggested that Return on Equity (ROE) emerges as the optimal variable chosen to define OP. In contradiction with Chakroun and Hmaied (2019) findings', the authors found that the ROE factor significantly improves the description of average returns, in China, while the Inv factor shows mixed results. However, the FM t-statistic for MC and B/M factors are highly significant. The authors concluded that a more accurate asset pricing model in the Chinese stock market is still necessary. At their turn, Alrabadi and Alrabadi (2018) confirmed the imperfection of the FF5F in pricing the variation in stock returns. In their study, the authors used pooled, fixed effect panel and random effect panel regressions and compared the predictive capability of CAPM, FF3F and FF5F models in Amman stock market. They found that intercepts are positively significant for the three-competing model. In line with Guo et al. (2017), Ali et al. (2019) confirmed their choice of ROE as the best selected variable indicating OP and, also, found that the ROE factor significantly improves the description of average returns whereas the Inv factor contributes marginally. However, the t-statistic in their FM regressions tend to be very small. The authors recommended the pursuit of an improved asset pricing model for the Pakistani stock market. In the Johannesburg stock exchange, Cox and Britten (2019) concluded that, even though there was a marginal improvement in the ability of FF5F to explain the cross-section of returns on most portfolios, the Inv premium appears to be ambiguous with regards to the FM tests. Studying five emerging Latin American markets (Brazil, Chile, Colombia, Mexico and Peru), de Carvalho et al. (2021) found that the β, MC and B/M factors are significant for all models tested. However, when the FF5F model was estimated, the coefficient for OP was significant only at the level of 10% and the Inv coefficient was not significant. In their FM second stage regression, they found that intercepts are highly significant in all cases which is in line with Alrabadi and Alrabadi (2018). In the same perspective, Hossain (2022) tried to analysis the explanatory power of common risk factors in area of FF3F vs FF5F in Dhaka Stock Exchange, Bangladesh. Using FM cross-sectional and time series regressions, the author confirmed the significance of all risk factors, with the exception of OP and Inv factors. However, as shown in several studies (e.g., Alrabadi and Alrabadi, 2018; de Carvalho et al., 2021), the problem of positively significant intercepts still persists.

The FF6F was also tested in several emerging markets. While studying 22 frontier equity markets, Zaremba and Maydybura (2019) documented the superiority of the FF6F over competing models as it explains the cross-sectional and time-series variation in returns. In addition, the authors emphasized strong momentum effect. In contradiction, Ali et al. (2019) found that the FF5F model outperforms all the other models considered including the FF6F model on all metrics in the Pakistan market. In the same market and from another perspective, Ali (2022) proposed an alternative four factor and concluded that it performed better than any other model under study including the FF5F and FF6F. Similarly to Zaremba and Maydybura (2019), Doğan et al. (2022) documented the superiority of FF6F in the Turkish stock market. They recommended investors the need to take account of the momentum factor as it allows higher returns to be obtained.

With respect to the Moroccan context, as far as we know, there is only one study which compared the predictive capability of the three rival models (CAPM, FF3F and FF5F) conducted by Alaoui Taïb and Benfeddoul (2023a). Using time series regressions, the authors emphasize that although the FF5F model outperforms its competitors, it falls short in providing a complete explanation for variations in returns. While examining the performance of the FF3F model, Aguenaou et al. (2011) opted to incorporate financial companies (in addition to non-financial ones) into their study sample. Their approach goes against FF's (1993) argument for excluding these stocks due to their high leverage. For their part, Tazi et al. (2022) examined the comparative performance of the Carhart four-factor and the FF3F models revealing that both models exhibit partial effectiveness in predicting returns on the Moroccan stock market (Benali et al., 2023). Lately, considering a different period of study, Alaoui Taïb and Benfeddoul (2023b) confirmed the dominance of the FF3F model in pricing the time-series of stock returns. However, it fails to account for a portion of the variation in Moroccan stock returns.

3. DATA AND METHODOLOGY

3.1. Data

The study data is extracted from the Refinitiv database supplemented by the website of Moroccan stock exchange. The analyzed period spans from July 2008 to June 2020, totaling 144 months. In conformity with the literature, the studied sample includes all Moroccan traded stocks, excluding financials and firms with negative B/M, for which the required data is available. For the purpose of estimating, especially the individual pre-ranking βs and the post-ranking βs (see below), we used a strongly balanced data. Thus, 45 firms are considered to meet the required selection criteria.

On a monthly basis, stock returns are calculated by including capital gains and dividends yields. In order to estimate βs in our first approach tests, we considered the reference portfolio, or market portfolio, as the net return of the MASI[2] index calculated each month (R_m), based on Refinitiv data. The research employs the monthly rate equivalent to the 13-week treasury bill rate, accessible via the Bank Al-Maghrib's website, as a proxy for the risk-free rate.

The explanatory variables included in our tests consist of MC, B/M, OP, Inv, and Mom. In the FF3F model, the MC and B/M are studied alongside β to explain stock returns. The FF5F model expands on this by including to β the additional variables MC, B/M, OP, and Inv, Finally, the FF6F model incorporates all the aforementioned variables (β, MC, B/M, OP, Inv) along with Mom. The definitions of these variables remain unchanged from Fama and French (1992, 1993, 2006, 2015, 2018). Also, we respect the 6-month lag for the construction of accounting variables. Thus, the data for stocks from December of year t-1 is linked to the monthly returns from July of year t to June of year t+1. Meanwhile, MC is measured from the month of June of year t. These annual values are considered stable over the 12 months between July of year t and June of year t+1. Additionally, according to Fama and French (1992), MC and B/M are tested using natural logarithm (ln).

3.2. Methodology for Estimating β

To assess and compare the predictive capability of factors in FF3F, FF5F, and FF6F models, the first empirical approach used in this study is carried out through an adaptation of cross-sectional methodologies from FM (1973) and Fama and French (1992). Given the precise measurement of MC, B/M, OP, Inv, and Mom for individual stocks, as Fama and French (1992) argued, there is no need to dilute the information in these variables by resorting to portfolios in the FM regressions. However, unlike directly observable variables, β coefficients need to be estimated beforehand. Hence, in consistent with Fama and French (1992), we estimate βs for portfolios and then assigning a portfolio's β to each individual stock within it. This methodology enables us to incorporate individual stocks into the FM asset-pricing tests.

Implementing this methodology in the study involves establishing three estimation periods. The first entails estimating individual β_is (pre-ranking βs) to construct portfolios. A subsequent period is necessary to estimate the β_ps of the formed portfolios (post-ranking βs). These βs will be used during the third period for cross-sectional tests, given that we attribute a portfolio's β_p to each individual stock within it.

Five portfolios[3] are created through the classification of stocks based on their pre-ranking individual β_is coefficients. In order to correct for the inherent non-synchronous trading stocks (Dimson, 1979), those βs are estimated as the sum of the slopes of the three regressor returns (lagged, contemporaneous, and lead) ($\beta_i=\beta_{i1}+\beta_{i2}+\beta_{i3}$)., In consistent with Alhashel (2019), the β_i values undergo additional adjustment to accommodate the autocorrelation of market returns. This involves dividing each β_i by 1 + 2AC, where AC represents the first-order autocorrelation of R_m. According to Heaney et al. (2016), these values are estimated as a time series over a rolling period[4] of 36 months using the following regression equation:

$$R_{it}-R_{ft}=\alpha_i+\beta_{i1}\left(R_{m(t-1)}-R_{f(t-1)}\right)+\beta_{i2}\left(R_{mt}-R_{ft}\right)$$
$$+\beta_{i3}\left(R_{m(t+1)}-R_{f(t+1)}\right)+\varepsilon \quad (1)$$

with,
R_{it}: Return of individual stock i for month t;
R_{ft}: Risk free rate for month t;
$R_{m(t-1)}$, R_{mt} and $R_{m(t+1)}$: Excess market return at lag one, contemporaneous and lead one, respectively, for month t;
α_i: Regression intercept for stock i;
β_{i1}, β_{i2} and β_{i3}: Lagged, contemporaneous, and lead coefficient βs, respectively, for stock i in the studied period;
ε: Error estimation.

The five portfolios of stocks are formed each month, from July 2011 to May 2020. These are designated as P1, P2, P3, P4, and P5. Hence, their β_p coefficients can be estimated over a new[5] rolling period of 36 months using the equation (1) by replacing individual stock returns with the equally-weighted return of each portfolio calculated in the month following its formation. The estimated post-ranking β_ps of the portfolios are subsequently assigned to the stocks constituting them. In other words, individual stocks receive, on a monthly basis, the β estimates from the corresponding portfolios to which they were assigned 3 years prior. Those βs are employed as the explanatory variable in the month-to-month cross-sectional regressions on individual stocks.

The Table 1 displays the average returns and the estimated βs of the five portfolios based on the pre-ranking βs over the period from July 2011 to May 2020.

Focusing on extreme return values, the obtained results appear consistent with the CAPM theory, which posits that the return of an asset increases with its risk. Indeed, we find that the returns of the riskiest portfolios (P5) exhibit a higher rate of return than those of the least risky portfolios (P1). However, this positive relationship with pre-ranking β coefficients varies randomly

2 Moroccan All Shares Index, the principal index of the Casablanca Stock Exchange.

3 Due to the limited size of our sample, we choose to form stocks into five portfolios instead of ten, FM (1973) and FF (1992), who deal with a larger number of stocks (Alaoui Taïb, 2014).

4 The first estimation covers the period from July 2008 to June 2011, the second from August 2008 to July 2011, and so on, totaling 108 successive estimations. The last possible estimation is carried out from June 2017 to May 2020 since the following month, the last one in the entire analysis period (June 2003), is reserved for the second stage.

5 The first estimation spans from July 2011 to June 2014, the second from August 2011 to July 2014, and so on. The last possible estimation is carried out from June 2017 to May 2020.

Table 1: Average returns of the five portfolios based on pre-ranking βs (July 2011-May 2020)

	R_p	Average of estimated β	β_{min}	β_{max}
P1	−0.001	−0.392	−10.227	0.527
P2	0.004	0.389	−0.288	0.859
P3	0.005	0.790	0.182	1.284
P4	0.004	1.266	0.458	2.006
P5	0.004	2.247	1.092	5.078

when considering the middle portfolios (P2, P3, and P4). Thus, this observation suggests that using β as a criterion for ranking stocks does not adequately control for the risk.

In Table 2, we present the average returns and characteristics of the five portfolios. These pertain to the estimated post-ranking βs of the portfolio and its attributes, including MC, B/M, OP, Inv, and Mom.

Results in Table 2 leads to similar observations as before. The positive relationship between returns and estimated βs coefficients is once again noted between the extreme portfolios (P1 and P5). However, when comparing the returns of the riskiest portfolios (P5) to those of the middle portfolios (P2, P3, and P4), the results show the lowest rate of return (0.0035). Beyond the inconsistent relationship between returns and risk, it seems that post-ranking βs and fundamental variables also exhibit unexpected correlations. In the case of MC, the estimated risk coefficients are positively correlated with MC as the risk increases as MC is larger. Similarly, and in contradiction to the literature, it appears that the estimated risk coefficients are positively correlated with the Inv variable. Regarding the B/M ratio, the findings show that the estimated βs are positively correlated with the ratio, which is in line with the literature review. This is not confirmed for the OP variable. Focusing on the extreme values of the portfolios, the results show an inverse relationship between the estimated risk coefficients and OP. When it comes to the Mom, the positive correlation with the estimated βs is shown only in the extreme values of the portfolios.

Table 3 compiles some descriptive statistics of the explanatory variables for individual stocks over the cross-sectional period from July 2014 to June 2020.

Unlike the estimated βs of stocks, which seem relatively undervalued in terms of average, the calculated values of the variables MC, B/M, OP, Inv, and Mom appear consistent. They are directly computed from the Refinitiv database, and therefore, their determination is more precise and less susceptible to measurement errors. Individually estimated βs through regression are indeed prone to measurement errors. The observation of the median value of post-ranking βs for the portfolios P3 and P4 in Table 2 suggests that it is the βs of extreme stocks that contribute to the undervaluation of their average βs. Grouping equally-weighted portfolios rather than individual stocks help reducing the estimation error of βs given the significant spread between β_{min} and β_{max} of portfolios (Table 1). However, extreme portfolios retain stocks with either overvalued or undervalued βs involving regression coefficients biased downward.

Table 2: Average returns, post-ranking βs and average characteristics of the five portfolios (July 2014-May 2020)

	R_p	β	MC (millions MAD)	B/M	OP	Inv	Mom
P1	−0.001	0.776	2 664, 636	0.705	0.159	0.040	0.051
P2	0.008	0.695	4 413, 839	0.703	0.183	0.044	0.088
P3	0.006	1.039	7 627, 821	0.728	0.199	0.032	0.060
P4	0.007	1.222	9 744, 264	0.835	0.181	0.037	0.117
P5	0.004	1.171	5 799, 210	0.864	0.133	0.045	0.105

Table 3: Descriptive statistics of the explanatory variables for individual stocks (July 2014 to June 2020)

	Average	Median	Standard deviation
β	0.981	1.013	0.318
MC (millions MAD)	6 049, 954	1 507, 268	16 981, 131
B/M	0.767	0.549	0.623
OP	0.192	0.171	0.255
Inv	0.040	0.014	0.181
Mom	0.084	0.037	0.422

3.3. Methodology for Estimating Coefficients of Explanatory Variables

The first methodology related stock returns to their individually calculated characteristics. The second one replaces the calculated values of the explanatory characteristics of stocks with their estimated coefficients. We opt for portfolios instead of individual stocks to reduce potential estimation errors associated with individual values. The regression tests make use of the three sets of six portfolios of dependent stocks as formed by Alaoui Taïb and Benfeddoul (2023a). We sorted portfolios based on MC and B/M, OP, Inv or Mom. From the MC sorting, stocks are split, using the median value, into two groups. Simultaneously, three groups are formed independently using the 40th and 20th percentiles for B/M ratio, OP, or Inv, and the 30th and 40th for Mom. The combination of each two sorting variables results in six MC-B/M portfolios, six MC-OP portfolios, six MC-Inv portfolios and six MC-Mom portfolios.

The models under examination (see below) estimate explanatory factors using the methodology adopted by FF (1993, 2015). Consistently with Alaoui Taïb and Benfeddoul (2023a), we independently constructed portfolios sorted on MC-B/M, MC-OP, MC-Inv, and MC-Mom following the 2×2 sorting method outlined in FF's (2015) second approach. Our choice is particularly motivated by the availability of data as well as the smaller number of firms trading in the Moroccan market.

The cross-sectional regression procedure is similar to the previous one, except that the time series estimates from the first step are extended here to include factors, in addition to the β factor. The test period spans from July 2008 to June 2020, during which the initial 3 years are excluded to allow for the necessary lag in estimating risk explanatory coefficients. The dependent variable is the monthly excess return of the portfolios. The explanatory variables include the estimated risk coefficients associated with the factors in each model under consideration.

An initial set of time-series regressions is carried out on the dependent portfolios to obtain risk estimates. More precisely, monthly excess returns of the portfolios are regressed on the explanatory variables of the FF3F, FF5F, and FF6F models. The regressions are performed over a rolling period of 3 years (36 months) with a 1-month lag for each repeated regression.

The series of estimated coefficients from this first step then serve as explanatory variables for the 108 cross-sectional regressions. The monthly excess returns of each of the twenty-four portfolios are regressed, month by month, on their risk estimators in the model from July 2011 to June 2020.

3.4. Models

3.4.1. FF3F model

In the case of FF3F, the coefficients β (Mkt), s (SMB) and h (HML), are estimated in time series over a rolling period of 36 months preceding the month of cross-sectional estimation. The time series regression is conducted according to the equation below:

$$R_{pt} - R_{ft} = \alpha_p + \beta_P\, MKT + s_p\, SMB + h_p\, HML + \varepsilon \tag{2}$$

$t \subset$ {July 2008,……, May 2020}

The monthly excess returns of the twenty-four dependent portfolios, separately, are explained by the three coefficients β, s and h, as follows:

$$R_{pt} - R_{ft} = \delta_0 + \delta_{MKT}\, \beta_P + \delta_{SMB} s_p + \delta_{HML}\, h_p + \varepsilon \tag{3}$$

$t \subset$ {July 2011,……, June 2020}

3.4.2. FF5F model

Regarding the FF5F model, the coefficients β (Mkt), s (SMB), h (HML), o (RMW) and iv (CMA) are estimated in time series over a rolling period of 36 months located just before the month of estimation. The time series regression is conducted according to the equation:

$$R_{pt} - R_{ft} = \alpha_p + \beta_P\, MKT + s_p\, SMB + h_p\, HML + o_p\, RMW + iv_p\, CMA + \varepsilon \tag{4}$$

$t \subset$ {July 2008,……, May 2020}

The monthly excess returns of the twenty-four dependent portfolios are then explained by the five coefficients: β, s, h, o and iv, as follows:

$$R_{pt} - R_{ft} = \delta_0 + \delta_{MKT}\, \beta_P + \delta_{SMB} s_p + \delta_{HML}\, h_p + \delta_{RMW}\, o_p + \delta_{CMA}\, iv_p + \varepsilon \tag{5}$$

$t \subset$ {July 2011,……, June 2020}

3.4.3. FF6F model

For the FF6F model, the coefficients β (Mkt), s (SMB), h (HML), o (RMW), iv (CMA), and UMD (d) are estimated in time-series over a rolling period of 36 months located just before the month of estimation. The time-series regression is conducted according to the equation:

$$R_{pt} - R_{ft} = \alpha_p + \beta_P\, MKT + s_p\, SMB + h_p\, HML + o_p\, RMW + iv_p\, CMA + d_p\, UMD + \varepsilon \tag{6}$$

$t \subset$ {July 2008,……, May 2020}

The monthly excess returns of the twenty-four dependent portfolios are then explained by the six coefficients: β, s, h, o, iv, and d, as follows:

$$R_{pt} - R_{ft} = \delta_0 + \delta_{MKT}\, \beta_P + \delta_{SMB} s_p + \delta_{HML}\, h_p + \delta_{RMW}\, o_p + \delta_{CMA}\, iv_p + \delta_{UMD}\, d_p + \varepsilon \tag{7}$$

$t \subset$ {July 2011,……, June 2020}

3.5. Methodology for Estimating Rd Returns of Individual Stocks

The basic FM approach could become problematic when factor loadings are measured with errors (Chordia et al., 2009). To circumvent such issues, we employ R_d returns as the dependent variables according to Brennan et al. (1998). Risk adjustment is done in three different ways using the FF3F (1993), the FF5F (2015), and the FF6F (2018). For each month, R_d returns are computed as the sum of the intercept and the residuals. For robustness and in consistent with Chordia et al. (2009), we get rolling estimates of the factor slopes (β, s, h, o, iv, d), for each month for all stocks utilizing the time series of the preceding 36[6] months in equation (2), (4), and (6). Considering the data for the current month, from FF3F, FF5F, and FF6F models, and the factor slopes generated for all stocks, we can compute the R_d return as follows:

Following equation (2), the R_d return from the three-factor model, is written:

$$R_d = (R_{it} - R_{ft}) - (\beta_i MKT + s_i SMB + h_i HML) = \alpha_i + \varepsilon \tag{8}$$

From equation (4), the R_d return from the five-factor model, is written:

$$R_d = (R_{it} - R_{ft}) - (\beta_i MKT + s_i\, SMB + h_i\, HML + o_p\, RMW + iv_p\, CMA) = \alpha_i + \varepsilon \tag{9}$$

Based on equation (6), the R_d return from the FF6F model, is written:

$$R_d = (R_{it} - R_{ft}) - (\beta_i MKT + s_i SMB + h_i HML + o_p RMW + iv_p CMA + d_p UMD) = \alpha_i + \varepsilon \tag{10}$$

Afterward, we conduct the FM (1973) regressions of these R_d

6 Due to the larger study period (324 months), Chordia et al. (2009) used a rolling period of the past sixty months (at least twenty-four months). It isn't the case of the current study as the sample period is 144 months. Thus, we choose 36 months rolling period as to be in accordance with our previous tests' considerations. (Heaney et al., 2016)

returns onto, firstly, MC and B/M; secondly, MC, B/M, OP, and Inv; and thirdly, MC, B/M, OP, Inv, and Mom, since these variables were identified as possessing predictive power for returns. The test period spans from July 2008 to June 2020, during which the initial 3 years are excluded to allow for the necessary lag in estimating R_d return.

Brennan et al. (1998) highlighted the potential for bias in the FM estimates of characteristic coefficients if there exists correlation between the characteristics and the error in factor slopes. When such dependency is present, Brennan et al. (1998) point out that the factors (employed for risk adjustment) become correlated with the time series of estimated coefficients. The bias may be important, particularly, for the Moroccan market, considering the plausibility that estimated loadings for small firms may be affected by illiquidity (Basiewicz and Auret, 2010).

Hence, Brennan et al. (1998) recommend a method that adjusts for this bias through the following equation:

$$\delta_j = \theta_j + \gamma f \tag{11}$$

Essentially, equation (11) represents a time-series regression of characteristic coefficients, calculated in each cross-sectional regression, onto factors (f) of the specified model (FF3F, FF5F or FF6F). The unbiased estimate of characteristic coefficient corresponds to the intercept term (θ_j) in the aforementioned regression and we focus in its t-statistic for interpretation. We use the Newey and West (1987) technique in the time-series regression.

4. RESULTS AND DISCUSSION

It is worth noting that the regression constant and the determination coefficients (R^2) are often overlooked because they are not only insufficient for assessing the model quality but also because their interpretation is delicate in cross-sectional analysis. Referring to the study of FF (1992), the authors focused in their interpretations solely in regression average slopes of MC and B/M factors. Therefore, the results related to these parameters do not represent essential criteria in the evaluation of the tested combinations of explanatory variables. Consistent with FF (1992) findings, we mainly focus on the characteristics in the tests' interpretation below. The β factor coefficient is consistently insignificant in both the first and the second cases. This result is not surprising, as it is widely reported in the literature on cross-sectional tests of stock returns (FF, 1992; Alaoui Taïb, 2014; Zada et al., 2017; Zada et al., 2018; Alhashel, 2019).

4.1. An examination of the Relationship between the Individual Stocks Returns and their Characteristics

The cross-sectional regression for individual stocks is conducted on a monthly basis from July 2014 to June 2020 (72 months). The monthly excess returns of stocks are regressed cross-sectionally on their estimated post-βs and on their characteristics from the model. In addition to the initial combinations of FF3F, FF5F, and FF6F models that we compare, other regressions with one, two, three, or four factors are performed. The objective is to examine the role of each explanatory variable in explaining stock returns and assess its robustness in the presence or absence of other possible competing variables. A good explanatory variable should exhibit a consistent level of significance in all cases. This should enable us to shed light on the true explanatory power associated with each variable in the Moroccan context.

The FM regression coefficients specific to the studied variables, ultimately, form time series. The average of these coefficients provides a measure of the variable's role in return formation. In other words, the averages of the cross-sectional regression slopes help identify the explanatory risk factors able to explain the Moroccan stock returns.

The statistical significance of the average coefficients of variables is assessed using the t-statistic (the average slope divided by its time series standard error) as defined by FF (1992).

Table 4 shows results obtained from unifactorial regressions (Panel A) and the different combinations in multifactorial regressions (Panel B).

Our single-factor model results reveal that the Mom variable has the most significant explanatory power for stock returns at 1%. While the Inv variable also exhibits a statistically significant coefficient at the 10% level, the remaining variables lack such significance. However, its effect on return is inconsistent with the literature, given its positive regression slope. The results from the two-factor modeling cross-sectional regressions show that the Inv variable maintain the same level of significance except when it is tested jointly with OP or Mom. Considering combinations with more than two variables, the Inv loses its explanatory power. This result is confirmed by Guo et al. (2017), who found that the Inv variable, measured in various ways, shows mixed results in the Chinese market.

It is noteworthy that the OP has significantly, at 5% level, improved its ability to describe stock returns in the presence of MC in the tested combination. Despite being significant only at the 10% level, the OP factor persistently enhances its explanatory capacity in returns across different multifactor combinations, especially when B/M is omitted (Nichol and Dowling, 2014; de Carvalho et al., 2021). Nevertheless, coefficients of the latter do not show any significant improvement, indicating that the descriptive capacity of the OP variable disappears without any apparent reason. Despite the small values of the FM t-statistic, Guo et al. (2017) concluded that the OP factor significantly improves the description of Chinese average returns, however, the Inv factor makes marginal contributions. For their part, the ROE is the best selected variable indicating OP (Ali et al., 2019).

Among the different combinations, there is little evidence of a negative relationship between the MC variable and stock returns, as its coefficient consistently appears insignificant in all cases. Conversely, the sign of the coefficient of B/M factor sounds, mostly, in contradiction to the literature. In addition, it exhibits an absent role in explaining stock returns. Those findings are in

Table 4: Average slopes (and, t-statistics) from month-by-month regressions of individual stock returns on explanatory variables (July 2014 to June 2020)

δ_{β}	δ_{MC}	$\delta_{B/M}$	δ_{Op}	δ_{Inv}	δ_{Mom}	$t(\delta_{\beta})$	$t(\delta_{MC})$	$t(\delta_{B/M})$	$t(\delta_{Op})$	$t(\delta_{Inv})$	$t(\delta_{Mom})$
Panel A : unifactorial regressions											
−0.00020						−0.03					
	−0.0003						−0.34				
		−0.0002						−0.08			
			0.0154						−1.41		
				0.0216***						−1.82	
					0.0223*						2.65
Panel B : multifactorial regressions											
0.0009	−0.0003					−0.16	−0.25				
0.0009		−0.0005				−0.17		−0.18			
0.0011			0.0152			−0.17			−1.35		
0.0001				0.0206***		−0.02				−1.72	
−0.0004					0.0216**	−0.06					2.51
	−0.0012	−0.0027					−0.74	−0.64			
	−0.0016		0.0255**				−1.45		−2		
	−0.0004			0.0204***			−0.39			−1.71	
	−0.0003				0.0238*		−0.31				2.84
		0.0021	0.0202					−0.67	−1.54		
		−0.0001		0.0209***				−0.04		−1.74	
		−0.0006			0.0236*			−0.21			2.81
			0.0151	0.0101					1.37	0.76	
			0.0118		0.0189**				1.09		2.14
				0.0159	0.0202**					1.38	2.34
0.0009	−0.0012	−0.0030				0.16	−0.74	−0.7			
0.0015	−0.0015		0.0251***			0.24	−1.41		1.9		
0.0009	−0.0003			0.0196***		0.15	−0.32			1.66	
0.0010	−0.0002				0.0230*	0.17	−0.18				2.69
0.0022		0.0015	0.0184			0.36		0.48	1.37		
0.0010		−0.0004		0.0199		0.17		−0.14		1.62	
0.0008		−0.0009			0.0231*	0.14		−0.35			2.69
0.0014			0.0149	0.0090		0.22			1.3	0.67	
0.0005			0.0124		0.0184**	0.09			1.11		2.08
−0.0002				0.0151	0.0196**	−0.04				1.33	2.23
	−0.0019	−0.0016	0.0200				−1.23	−0.36	1.53		
	−0.0011	−0.0024		0.0195***			−0.71	−0.57		1.66	
	−0.0011	−0.0028			0.0235*		−0.75	−0.72			2.85
	−0.0014		0.0244***	0.0081			−1.36		1.93	0.62	
	−0.0012		0.0188		0.0196**		−1.08		1.48		2.21
	−0.0004			0.0142	0.0219**		−0.36			1.26	2.58
		0.0016	0.0190	0.0081				0.52	1.45	0.61	
		0.0001	0.0110		0.0199**			0.03	0.82		2.21
	−0.0006			0.0145	0.0218**		−0.22			1.25	2.55
			0.0128	0.0066	0.0182**				1.15	0.52	2.07
0.0025	−0.0020	−0.0023	0.0185			0.43	−1.33	−0.54	1.37		
0.0009	−0.0011	−0.0027		0.0188		0.16	−0.73	−0.65		1.6	
0.0008	−0.0011	−0.0031			0.0228*	0.14	−0.73	−0.8			2.7
0.0016	−0.0014		0.0242***	0.0074		0.26	−1.33		1.83	0.56	
0.0014	−0.0011		0.0190		0.0191**	0.22	−1.01		1.45		2.13
0.0007	−0.0003			0.0139	0.0212**	0.13	−0.24			1.26	2.45
0.0024		0.0010	0.0174	0.0069		0.4		0.31	1.29	0.51	
0.0023		−0.0006	0.0093		0.0198**	0.39		−0.2	0.67		2.19
0.0006		−0.0009		0.0138	0.0213**	0.11		−0.36		1.22	2.45
0.0008			0.0132	0.0055	0.0178**	0.14			1.16	0.43	2.03
	−0.0018	−0.0019	0.0192	0.0061			−1.23	−0.43	1.47	0.48	
	−0.0019	−0.0034	0.0117		0.0195**		−1.32	−0.83	0.88		2.2
	−0.0012	−0.0028		0.0129	0.0219*		−0.77	−0.71		1.14	2.6
	−0.0012		0.0193	0.0048	0.0191**		−1.06		1.49	0.39	2.16
		−0.0001	0.0116	0.0046	0.0196**			−0.03	0.85	0.37	2.19
0.0027	−0.0020	−0.0027	0.0180	0.0049		0.45	−1.33	−0.62	1.33	0.38	
0.0027	−0.0020	−0.0042	0.0103		0.0191**	0.47	−1.4	−1.06	0.75		2.14
0.0005	−0.0011	−0.0031		0.0126	0.0211**	0.1	−0.77	−0.8		1.13	2.46
0.0014	−0.0011		0.0194	0.0042	0.0186**	0.23	−1		1.45	0.34	2.09
0.0025		−0.0009	0.0098	0.0035	0.0195**	0.42		−0.27	0.69	0.28	2.17
	−0.0019	−0.0034	0.0126	0.0025	0.0192**		−1.31	−0.85	0.93	0.21	2.17
0.0028	−0.0020	−0.0043	0.0113	0.0015	0.0188**	0.48	−1.4	−1.07	0.8	0.12	2.11

(*), (**) and (***) represent significance levels of 1%, 5%, and 10%, respectively

contradiction with Guo et al. (2017) who found highly FM t− statistic for both MC and B/M.

The Mom factor emerges as the clear winner. It surpasses its competitors in several ways. Firstly, the Mom variable exhibits a consistently significant coefficient across various model specifications and combinations. This significance level typically falls within a range of 1% to 5%, indicating a strong and reliable explanatory power for stock returns. In simpler terms, Mom is not just a random influence; it has a statistically robust relationship with stock performance. Secondly, the Mom coefficient carries the expected positive sign. This aligns with the established concept of Mom: stocks with strong past upward trends tend to continue performing well, while those experiencing downward trends might see further declines. This positive sign reinforces the idea that Mom captures a genuine trend in stock prices, not just random fluctuations. Finally, these findings suggest that Mom retains valuable information about future stock returns. It appears to capture a persistent trend that helps predict future performance.

Our findings presented in Table 4 reveal a surprising divergence from the established results of the FF framework (1992, 1993, 2006, 2015, 2018). The three models we evaluated do not support the notion that traditional characteristics namely MC, B/M, OP, and Inv significantly explain variations in stock returns within the Moroccan context. This stands in contrast to the broader market observations documented by the authors, where these factors often play a prominent role. Our analysis of various factor combinations in Table 4, including the traditional FF3F, FF5F models along with the FF6F combination, reinforces this point. None of the factors, with the exception of Mom, exhibit statistically significant explanatory power for stock returns variations in the Moroccan market. The sole exception to this trend is the Mom factor, which consistently emerges as a particularly prominent force in explaining stock returns within our analysis.

4.2. An Examination of the Relation between Portfolios' Returns and the Coefficients of Explanatory Variables

The results of the cross-sectional regression coefficients in the second stage provide, for each model, the average coefficients of the risk factors. The t-statistics for these coefficients are calculated in the same manner as FF (1992). Their significance allows for the assessment of explanatory variables in the model.

4.2.1. FF3F model

Table 5 presents the cross-sectional regression results for the FF3F model.

When it comes to MC-B/M portfolios, the average estimates of the risk premiums are not significant, except for SMB. Panel A shows that the t-statistic is <2 standard deviations. However, the coefficient displays a positive sign which is contrary to the literature. The 108 cross-sectional regressions, indeed, lead to average estimates that are not significant when MC-OP, MC-Inv or MC-Mom portfolios are taken as dependent variables for any risk premium. The addition of MC and B/M variables to β does not improve its risk estimator, and the results of the three factors combined in the asset pricing model are almost not satisfactory. In contradiction to those findings, de Carvalho et al. (2021) found that all the average slopes from month-by-month regressions of LHS portfolios' returns on coefficients of FF3F explanatory variables were highly significant in five Latin American markets.

4.2.2. FF5F model

Table 6 presents the results of the cross-sectional regression results for the FF5F model.

The average estimates of the risk premiums are generally statistically non-significant (Ali et al., 2019). The addition of OP and Inv to the FF3F model does not enhance the explanatory power of the β, MC, and B/M variables. On the contrary, their roles disappear, except for MC in the case of portfolios sorted on MC-OP. However, the coefficient displays a positive sign contrary to the literature. This positive sign is also documented by Chakroun and Hmaied (2019) in the French market. The authors found that across all the three considered portfolio sets (MC-B/M, MC-OP, and MC-Inv), the

Table 5: Average slopes (t-statistics) from month-by-month regressions of portfolios' returns on coefficients of FF3F explanatory variables (July 2011 to June 2020)

	δ_{Mkt}	δ_{SMB}	δ_{HML}
Panel A: MC-B/M			
Coefficient	−0.004	0.010**	0.003
t-statistic	−0.352	2.172	0.624
Panel B: MC-OP			
Coefficient	0.003	0.005	−0.004
t-statistic	0.222	1.163	−0.811
Panel C: MC-Inv			
Coefficient	0.000	0.007	−0.009
t-statistic	−0.006	1.458	−0.822
Panel D: MC-Mom			
coefficient	−0.007	0.007	0.012
t-statistic	−0.750	1.330	1.660

(*), (**) and (***) represent significance levels of 1%, 5%, and 10%, respectively

Table 6: Average slopes (t-statistics) from month-by-month regressions of portfolios' returns on coefficients of FF5F explanatory variables (July 2011 to June 2020)

	δ_{Mkt}	δ_{SMB}	δ_{HML}	δ_{RMW}	δ_{CMA}
Panel A: MC-B/M					
Coefficient	0.047	0.029	0.014	0.204	0.076
t-statistic	0.462	1.544	0.615	1.061	0.979
Panel B: MC-OP					
Coefficient	−0.079	0.018**	−0.034	0.011	0.006
t-statistic	−0.371	2.428	−1.242	0.610	0.111
Panel C: MC-Inv					
Coefficient	0.128	0.017	−0.002	0.157	0.004
t-statistic	0.844	0.220	−0.007	0.979	0.180
Panel D: MC-mom					
coefficient	−0.053	−0.096	0.121	−0.077	0.054
t-statistic	−0.220	−0.810	0.960	−0.370	0.550

(*), (**) and (***) represent significance levels of 1%, 5%, and 10%, respectively

average estimates of SMB are positively signed but statistically insignificant. While conducting month-by-month cross-sectional regressions of individual stocks traded on the Dhaka Stock Exchange, Hossain (2022) concluded that all of the average estimates were significant except for those related to OP and Inv variables.

4.2.3. FF6F model

From Table 7, the cross-sectional regression results for the FF6F model presented trends similar to those of the FF5F model in Table 6.

The average estimate of all risk premiums for generally lacked statistical significance with the exception of SMB risk premium in portfolios sorted on MC-OP. The addition of the Mom variable to the FF5F model did not generally enhance the explanatory power of the existing variables. Panel D reinforces the importance of Mom. Here, the average estimate related to the Mom variable is statistically significant at the 5% level. Furthermore, the positive sign of the coefficient aligns with established market theory, indicating that stocks with strong past upward trends tend to continue performing well in the Moroccan context.

The issue of errors in the variables seems to persist in the three, five and six factor modeling. Explanatory variables used in cross-sectional tests are the result of previous time-series estimations that are affected by errors. The final result is inevitably impacted.

Table 7: Average slopes (t-statistics) from month-by-month regressions of portfolios' returns on coefficients of FF6F explanatory variables (July 2011 to June 2020)

	δ_{Mkt}	δ_{SMB}	δ_{HML}	δ_{RMW}	δ_{CMA}	δ_{UMD}
Panel A: MC-B/M						
Coefficient	−0.016	0.007	−0.001	−0.006	−0.009	−0.012
t-statistic	−0.900	1.540	−0.180	−0.009	−0.890	−0.650
Panel B: MC-OP						
Coefficient	0.001	0.012**	−0.011	0.000	−0.013	0.024
t-statistic	0.030	2.330	−0.760	0.030	−1.130	1.330
Panel C: MC-Inv						
Coefficient	0.012	0.012	−0.023	−0.013	0.003	0.002
t-statistic	0.630	1.340	−0.930	−0.400	0.620	0.070
Panel D: MC-Mom						
Coefficient	0.042	0.015	0.034	0.011	−0.026	0.034**
t-statistic	1.060	1.420	0.860	0.350	−1.550	2.390

(*), (**), and (***) represent significance levels of 1%, 5%, and 10%, respectively

4.3. An Examination of the Relationship between the Individual Stocks R_d Returns and their Characteristics

Our third analysis employs the Brennan et al. (1998) approach, specifically addressing the errors-in-variables issue by computing R_d returns for incorporation into cross-sectional regressions as the dependent variable. As mentioned earlier, we adjusted stock returns using the FF3F, the FF5F, and the FF6F models, as these models have demonstrated, in the literature, predictive power for stock returns. To ensure that the model used in risk adjustment is complete, the adjusted coefficients of characteristics should be insignificant. If they exceed zero, it suggests that those characteristics persist in having explanatory power, thereby rejecting the tested model.

Table 8 shows cross-sectional regression results of pricing errors (the sum of intercept and residuals) of individual stocks onto the characteristics of each model included. The model's ability to price out characteristics directly attests to its validity.

In Panel A, under the FF3F adjustment, the univariate regression shows that the adjusted coefficient on MC is close to zero, suggesting that the model is pricing out this firm characteristic, contrary to B/M. However, the positive sign of its coefficient contradicts the literature. When tested jointly with B/M, the adjusted coefficient of the MC variable shows the correct sign, but it is no longer different from zero. Although the B/M effect somewhat diminishes after being tested jointly with MC, it remains robust. Even after controlling for FF3F factor loadings, firm characteristics retain their predictive power for returns. Similarly, Basiewicz and Auret (2010) found that, when tested jointly, the adjusted coefficient of MC remains negatively significant in the Johannesburg Stock Exchange. However, the B/M effect dissipates after FF3F risk adjustment.

With the use of FF5F adjustment (Panel B), the MC coefficient still shows an insignificant value, in the univariate regression, but this

Table 8: Results of monthly cross-sectional regression of R_d returns against firm characteristics (July 2011 to June 2020)

θ_{MC}	$\theta_{B/M}$	θ_{OP}	θ_{Inv}	θ_{Mom}	$t(\theta_{MC})$	$t(\theta_{B/M})$	$t(\theta_{OP})$	$t(\theta_{Inv})$	$t(\theta_{Mom})$
Panel A: FF3F adjustment									
0.018					0.95				
	−0.234*					−9.14			
−0.099*	−0.432*				−2.92	−5.98			
Panel B : FF5F adjustment									
−0.020					−0.89				
	−0.066**					−2.20			
		0.767*					3.57		
			0.099					0.37	
−0.083*	−0.069	1.047*	−0.069		−2.92	−0.73	3.69	−0.73	
Panel C : FF6F adjustment									
−0.021					−0.90				
	−0.070*					−2.61			
		0.762*					3.69		
			0.082					0.34	
				0.123					1.06
−0.084*	−0.068	1.030*	−0.022	0.123	−2.73	−0.69	3.68	−0.09	1.06

(*), (**) and (***) represent significance levels of 1%, 5%, and 10%, respectively

time its negative sign aligns with the literature. Similar results are found for the Inv variable. The univariate regression shows that its coefficient is close to zero implying that the model is pricing out this firm characteristic. However, it maintains its positive sign showed in the earlier tests. For its part, the B/M coefficient still holds its significant value with a negative sign. The model demonstrates relatively improved performance in capturing the OP effect, with a smaller but still significant coefficient. The average cross-sectional regression coefficients using jointly and directly the characteristics including FF5F model are not generally satisfactory. Regarding the MC variable, results are similarly seen from Panel A. Although maintaining its negative sign, the coefficient become significant. However, in the case of the B/M variable, its coefficient preserves its negatively insignificant sign. There is no observed improvement in the adjusted coefficient of the OP variable. Testing jointly with other variables does not change the significance of the OP coefficient found in the univariate regression. The Inv variable deserves notice. There is a remarkable improvement in the sign of the coefficient. It is now negatively insignificant.

In Panel C, after adjusting with the FF6F model, the coefficient for MC remains statistically insignificant in the univariate regression, with the expected negative sign. The B/M coefficient also maintains its significance, retaining a negative sign. Similarly, the OP variable remains statistically significant. The Inv variable shows an insignificant coefficient, indicating that the model is pricing out this firm characteristic. Nevertheless, its positive sign seen in previous tests persists. The univariate regression shows that the adjusted coefficient on Mom is close to zero. In addition, the positive sign of its coefficient aligns with the literature.

The average cross-sectional regression coefficients using jointly and directly all the variables including FF6F model are not generally satisfactory. Concerning the MC variable, results are consistent across Panel A and Panel B, where despite maintaining a negative sign, the coefficient becomes significant. However, for the B/M variable, its coefficient remains insignificantly negative. There is no observed enhancement in the adjusted coefficient for the OP variable, even when jointly tested with other variables, indicating its persistent significance found in the univariate regression. The improvement in the coefficient's sign of the Inv coefficient remains evident from Panel B. The Mom variable retains its positively insignificant coefficient, suggesting the model "absorbs" the Mom effect.

Across all the considered models, the Brennan et al. (1998) methodology reveals that even after adjusting for model risk, some effects persist. This suggests that the adjusted cross-sectional regression coefficients, estimated using the variables included in each model jointly and directly, are not satisfactory. In other words, the risk adjustment using the asset pricing errors from all the competing models appears incomplete, leading to the rejection of the models.

5. CONCLUSION

This study tested the explanatory power of the β factor, firm fundamental characteristics (MC, B/M, OP and Inv), and Mom variable over expected returns for a sample of non-financial Moroccan firms from July 2008 to June 2020. We analyzed the role of each explanatory variable through three different methodologies. Drawing on the work of FM (1973) and FF (1992), our first test involves cross-sectional regression of the monthly excess returns of individual stocks on their estimated post-βs and on their calculated variables from FF3F, FF5F, and FF6F models. The second methodology tends to replace the calculated values of the explanatory variables of stocks with their estimated coefficients. We opt for portfolios instead of individual stocks to reduce potential estimation errors associated with individual values. Third, we specifically adjust for the errors-in-variables problem by applying the Brennan et al. (1998) methodology. We calculate the R_d individual stocks returns for inclusion in cross-section regression as dependent variable.

Based on the first two methodologies, the role of the β factor in explaining cross-sectional Moroccan returns seems to be absent as its coefficient is consistently non-significant. This aligns with many studies in financial literature. The absence of explanatory power for β could be attributed to the "errors-in-variables" problem common in two-step methodology of Fama and MacBeth (1973). This persistent issue across regressions prevents β from showing improvement in the various return models tested.

Generally, the Mom factor emerges as the most promising variable. Unlike the second methodology, results from the first methodology reveal that the Mom variable exhibits a consistently significant coefficient across various model specifications and combinations. In the third methodology, after adjusting with the FF6F model, the Mom variable retains its positively insignificant coefficient, suggesting that the model "absorbs" the Mom effect.

Ideally, a strong explanatory variable should exhibit consistent significance across different methodologies. For our case, the three models we evaluated do not support the notion that traditional characteristics namely MC, B/M, OP, and Inv significantly explain variations in stock returns within the Moroccan context. So, evidence on the role assigned to each variable tested in explaining Moroccan stock returns is sensitive to estimation methodologies.

While employing various statistical methodologies, traditional factors in standard models did not yield satisfactory results in explaining Moroccan stock return variations. Divergences in accounting standards and economic environments may influence how fundamental anomalies manifest in different stock markets. Traditional asset pricing models typically assume well-functioning, informationally efficient markets. However, emerging markets often deviate from these assumptions. They are characterized by information asymmetry, concentrated ownership structures, higher volatility, limited trading activity, smaller pool of investors, and lower overall market capitalization compared to developed markets. These deviations from the idealized market conditions can lead to limitations in the explanatory power of traditional asset pricing models when applied to emerging markets (Alrabadi and Alrabadi, 2018). This underscores the critical need to explore new factors and potentially develop a more appropriate asset pricing model better suited to the Moroccan context.

REFERENCES

Aguenaou, S., Abrache, J., El Kadiri, B. (2011), Testing the Fama French three factor model in the Moroccan stock market. International Journal of Business, Accounting, and Finance, 5(2), 57-66.

Alaoui Taïb, A. (2014), La Relation Entre Rentabilité et Risque des Titres Financiers. Paris: Presses Académiques Francophones.

Alaoui Taïb, A., Benfeddoul, S. (2023a), The empirical explanatory power of CAPM and the Fama and French three-five factor models in the Moroccan stock exchange. International Journal of Financial Studies, 11(1), 1-19.

Alaoui Taïb, A., Benfeddoul, S. (2023b), Explaining the time series of stock returns: Comparative study on the Moroccan market. Journal of Academic Finance, 14(2), 2-16.

Alhashel, B.S. (2019), Cross-section of returns in frontier markets: Evidence from the GCC markets. Emerging Markets Finance and Trade, 57(3), 798-823.

Ali, F. (2022), Testing mispricing-augmented factor models in an emerging market: A quest for parsimony. Borsa Istanbul Review, 22(2), 272-284.

Ali, F., Khurram, M.U., Jiang, Y. (2019), The five-factor asset pricing model tests and profitability and investment premiums: Evidence from Pakistan. Emerging Markets Finance and Trade, 57(9), 2651-2673.

Alrabadi, D.W.H., Alrabadi, H.W.H. (2018), The Fama and French five factor model: Evidence from an emerging market. Arab Journal of Administration, 38(3), 295-304.

Banz, R.W. (1981), The relationship between return and market value of common stocks. Journal of Financial Economics, 9(1), 3-18.

Basiewicz, P.G., Auret, C.J. (2010), Feasibility of the Fama and French three factor model in explaining returns on the JSE. Investment Analysts Journal, 71(1), 13-25.

Benali, M., Lahboub, K., Bouhadi, A. (2023), Pricing ability of Carhart four-factor and Fama-French three-factor models: Empirical evidence from Morocco. International Journal of Financial Studies, 11(20), 1-14.

Bhatnagar, C.S., Ramlogan, R. (2012), The capital asset pricing model versus the three factor model: A United Kingdom Perspective. International Journal of Business and Social Research, 2(1), 51-65.

Brennan, M.J., Chordia, T., Subrahmanyam, A. (1998), Alternative factor specifications, security characteristics, and the cross-section of expected stock returns. Journal of Financial Economics, 49(3), 345-373.

Campbell, J.Y., Lo, A.W., MacKinlay, A.C. (1997), The Econometrics of Financial Markets. United States: Princeton University Press.

Chai, D., Chiah, M., Gharghori, P. (2019), Which model best explains the returns of large Australian stocks? Pacific-Basin Finance Journal, 55, 182-191.

Chakroun, A.Z., Hmaied, D.M. (2019), Detecting profitability and investment risk premiums in the french stock market. Research in Finance, 35, 71-104.

Chen, L., Novy-Marx, R., Zhang, L. (2011), An Alternative Three-Factor Model (SSRN Scholarly Paper 1418117).

Chordia, T., Huh, S.W., Subrahmanyam, A. (2009), Theory-based illiquidity and asset pricing. The Review of Financial Studies, 22(9), 3629-3668.

Cox, S., Britten, J. (2019), The Fama-French five-factor model: Evidence from the Johannesburg stock exchange. Investment Analysts Journal, 48(3), 240-261.

de Carvalho, G.A., Amaral, H.F., Pinheiro, J.L., Correia, L.F. (2021), The pricing of anomalies using factor models: A test in Latin American markets. Revista Contabilidade e Financas, 32(87), 492-509.

Dimson, E. (1979), Risk measurement when shares are subject to infrequent trading. Journal of Financial Economics, 7(2), 197-226.

Doğan, M., Kevser, M., Leyli Demirel, B. (2022), Testing the Augmented Fama-French six-factor asset pricing model with momentum factor for Borsa Istanbul. Discrete Dynamics in Nature and Society, 2022(1), 3392984.

Fama, E.F., French, K.R. (1992), The cross-section of expected stock returns. The Journal of Finance, 47(2), 427-465.

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

Fama, E.F., French, K.R. (2006), Profitability, investment and average returns. Journal of Financial Economics, 82(3), 491-518.

Fama, E.F., French, K.R. (2008), Average returns, B/M, and share issues. The Journal of Finance, 63(6), 2971-2995.

Fama, E.F., French, K.R. (2015), A five-factor asset pricing model. Journal of Financial Economics, 116(1), 1-22.

Fama, E.F., French, K.R. (2017), International tests of a five-factor asset pricing model. Journal of Financial Economics, 123(3), 441-463.

Fama, E.F., French, K.R. (2018), Choosing factors. Journal of Financial Economics, 128(2), 234-252.

Fama, E.F., MacBeth, J.D. (1973), Risk, return, and equilibrium: Empirical tests. Journal of Political Economy, 81(3), 607-636.

Fletcher, J. (2019), Model comparison tests of linear factor models in U.K. stock returns. Finance Research Letters, 28, 281-291.

Foye, J. (2018), A comprehensive test of the Fama-French five-factor model in emerging markets. Emerging Markets Review, 37, 199-222.

Guo, B., Zhang, W., Zhang, Y., Zhang, H. (2017), The five-factor asset pricing model tests for the Chinese stock market. Pacific Basin Finance Journal, 43, 84-106.

Heaney, R., Koh, S., Lan, Y. (2016), Australian firm characteristics and the cross-section variation in equity returns. Pacific Basin Finance Journal, 37, 104-115.

Hossain, M.S. (2022), Asset pricing puzzle: New evidence of Fama-French five-factors in emerging market perspectives. Real Estate Management and Valuation, 30(3), 73-85.

Jiao, W. (2018), Exploring Risk Factors on Chinese a Share Stock Market-in the Frame of Fama-French Factor Model. Rennes: Université De Rennes. p1.

Kim, S., Skoulakis, G. (2018), Ex-post risk premia estimation and asset pricing tests using large cross sections: The regression-calibration approach. Journal of Econometrics, 204(2), 159-188.

Kubota, K., Takehara, H. (2018), Does the Fama and French five-factor model work well in Japan? International Review of Finance, 18(1), 137-146.

Lin, Q. (2017), Noisy prices and the Fama-French five-factor asset pricing model in China. Emerging Markets Review, 31, 141-163.

Mosoeu, S., Kodongo, O. (2020), The Fama-French five-factor model and emerging market equity returns. Quarterly Review of Economics and Finance, 85, 55-76.

Newey, W.K., West, K.D. (1987), A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica, 55(3), 703-708.

Nichol, E., Dowling, M. (2014), Profitability and investment factors for UK asset pricing models. Economics Letters, 125(3), 364-366.

Novy-Marx, R. (2013), The other side of value: The gross profitability premium. Journal of Financial Economics, 108(1), 1-28.

O'Connell, M. (2023), Model comparison in German stock returns. Journal of Economic Studies, 50(6), 1245-1259.

Roll, R. (1977), A critique of the asset pricing theory's tests Part I: On past and potential testability of the theory. Journal of Financial Economics, 4(2), 129-176.

Shah, S.H.A., Shah, A., Khan, M.K., Ullah, H. (2021), The risk and return relations: New evidence from Pakistani stock market. Journal of Accounting and Finance in Emerging Economies, 7(1), 1.

Sharpe, W.F. (1964), Capital asset prices: A theory of market equilibrium under conditions of risk. The Journal of Finance, 19(3), 425-442.

Stattman, D. (1980), Book value and stock returns. The Chicago MBA: A Journal of Selected Papers, 4(1), 25-45.

Tazi, O., Aguenaou, S., Abrache, J. (2022), A comparative study of the Fama-French three factor and the Carhart four factor models: Empirical evidence from Morocco. International Journal of Economics and Financial Issues, 12(1), 58-66.

Titman, S., Wei, K.C.J., Xie, F. (2004), Capital investments and stock returns. Journal of Financial and Quantitative Analysis, 39(4), 677-700.

Walkshäusl, C., Lobe, S. (2014), The alternative three-factor model: An alternative beyond US Markets? European Financial Management, 20(1), 33-70.

Xie, S., Qu, Q. (2016), The three-factor model and size and value premiums in China's stock market. Emerging Markets Finance and Trade, 52(5), 1092-1105.

Zada, H., Afeef, M., Arshad, H. (2017), Does Fama & French's five-factor model perform better than the capital asset pricing model and Fama & French's three-factor model? Evidence from an emerging equity market. Journal of Administrative and Business Studies, 2(2), 1-11.

Zada, H., Rehman, M., Khwaja, M. (2018), Application of Fama and French five factor model of asset pricing: Evidence from Pakistan stock market. International Journal of Economics, Management and Accounting, 16(1), 1-23.

Zaremba, A., Maydybura, A. (2019), The cross-section of returns in frontier equity markets: Integrated or segmented pricing? Emerging Markets Review, 38, 219-238.

Zhang, Z., Yu, Y., Ma, Q., Yao, H. (2022), A revised comparison between Fama and french five-factor model and three-factor model-based on China's a-share market. Journal of Advances in Applied and Computational Mathematics, 9, 168-180.