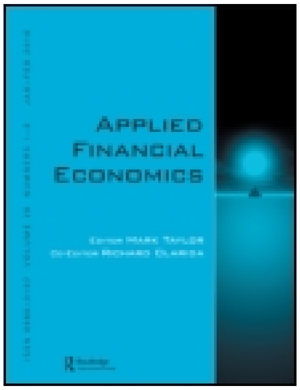

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Applying the CAPM and the Fama–French models to the BRVM stock market

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This article applies and compares two asset-pricing models – the Capital Asset Pricing Model (CAPM) and the Fama–French three-factor pricing model – on the stocks of 28 companies listed on the Bourse Régionale des Valeurs Mobilières (BRVM) for the period July 2001–December 2008. We find that 11 stocks satisfy the CAPM, and the market risk factor explains an average of only 11.32% of the excess stock return variations. When we apply the Fama–French model, we find that 10 of the 28 stocks satisfy the model's hypotheses and equations: for most of these securities, a CAPM-type model specification is rejected. When we add the size and book-to-market explanatory factors, the average adjusted R^2 increases to 20.40%. Both models, however, failed to explain the variations in returns of at least 60% of the stocks listed on this market.

Keywords: Africa; BRVM; CAPM; Fama–French model

JEL Classification: G12; G15

I. Introduction

In emerging markets, where savings have long been the main financing instrument for productive investments, developing stock markets are poised to play an increasing role in channelling capital investments to the economy. Dynamic stock markets will not only mobilize internal savings, but will also attract foreign investments. Emerging markets – especially African stock markets, whose correlation with developed stock markets is low – represent an excellent investment for foreign investors wishing to diversify their portfolio. The recent financial crisis has underscored this phenomenon, with many African stock markets experiencing very little turbulence while almost all developed stock markets were severely hit. Sophisticated investors would be well advised to profit from the weak efficiency and high returns of growing emerging markets.

But investors considering these opportunities are confronted with a lack of data on the factors that affect stock return variations in these stock markets.

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For this reason, this article examines the empirical validity and compares two asset-pricing models with regard to the stocks listed on the Bourse Régionale des Valeurs Mobilières (BRVM), the common stock market of the West African Economic and Monetary Union (WAEMU) located in Abidjan, Côte d'Ivoire. More specifically, we seek to identify factors that explain the stock returns of BRVM-listed companies. We retain two models commonly used in the literature: (1) the Capital Asset Pricing Model (CAPM), and (2) the three-factor Fama–French (FF) pricing model (Fama and French, 1992, 1993). Although extensive research have applied these models and their extensions on data from developed stock markets, very few studies have been devoted to African stock markets, especially the BRVM. It is therefore unclear how the models would behave in the presence of the BRVM's many imperfections: the smaller size of listed companies, the poor governance structure, limitations in financial services, the weak quality of information disclosure, inadequate investor protection mechanisms, large operational risks, substantial delays in payment-delivery processing, etc. In addition to these difficulties, West Africa has experienced several cycles of political instability that have affected the business environment. These imperfections justify empirically applying pricing models that have by and large worked well in developed stock markets, in the context of the BRVM.

We use monthly stock price data from the BRVM from July 2001 to December 2008. Among the 28 stocks considered, only 11 (39.29%) satisfy the CAPM. The market risk factor explains only 11.32% of stock returns variations. With the FF, 10 of the 28 stocks studied satisfy the model's hypotheses and equations: this represents 35.71% of stocks and an average adjusted-R^2 of 20.40%. For most of these securities, a CAPM-type model specification is rejected. Both models, however, failed to explain the variations in returns of more than 60% of the stocks listed on this market.

The rest of this article is structured as follows. The next section presents the data and the methodology used for our study and discusses the results of our empirical estimations. We then conclude in the last section.

II. Empirical Analyses

We use 7 years of monthly stock prices of companies listed on the BRVM (July 2001 to December 2008).[1] To be included in the sample, the firm must have been listed on the stock market in December 2000 and remained listed until December 2008.[2] From the 37 stocks satisfying these criteria, we excluded nine that were less liquid than the others.[3] The list of companies retained for the sample and their ticker symbols are given in the Appendix.

Stock returns are calculated as follows:

$$R_{j,t} = \ln\left(\frac{P_{j,t}}{P_{j,t-1}}\right)$$

where R_{jt} is the monthly return of stock j for the month t and P_{jt} is the average price of stock j over the month t.[4] The market return is the total return of the BRVM composite index. The risk-free interest rate is proxied by the money market rate obtained from the Central Bank of West African States (BCEAO).[5] This rate has the advantage of reliability, as regional banks use it to calculate spreads.

Construction of the factors portfolios

Size value in the year t is calculated based on the values in the month of June of the year t as follows: the number of shares available in June, times the stock price on the last day of June. Book-to-market ratio in the year t is calculated with data from December $t-1$ as follows: the book value of year-end $t-1$ according to the financial statements available in the year t, divided by the market capitalization calculated using the share price on the last day of December $t-1$. Size (market capitalization at June t) and book-to-market ratio (at December $t-1$) are

[1] We consider monthly data rather than daily data because of the liquidity issue: certain months count several days when most stocks do not trade.
[2] Note that there may exist a survivorship bias since we only consider stocks that have been around since 2000.
[3] We exclude nine stocks that have not been traded for more than 30 days over the 90 months of the study period.
[4] In all stocks considered, the dividends are paid mostly at the end of the year; we therefore exclude the dividends from the calculation of the returns to avoid having outliers for the month of December.
[5] For each month, we associate the interbank rate with 1-month maturity. Because WAEMU is a regional economic community, this rate can be applied uniformly across member countries. Government T-Bill rates, in contrast, are also country-specific.

Table 1. Formation of the six portfolios

	Small market cap	Big market cap
30% High book-to-market	Small-Value	Big-Value
40% Median book-to-market	Small-Neutral	Big-Neutral
30% Low book-to-market	Small-Growth	Big-Growth

used to construct the factors for the period from July t to June $t+1$.[6]

The small minus big (SMB) and high minus low (HML) portfolios are constructed following the approach of Fama–French described on Kenneth French's website.[7] The six portfolios used to calculate the SMB and HML portfolios are formed at the end of each June. We begin by forming two groups of portfolios based on the median market capitalization: a small market capitalization group versus a large market capitalization group. For each group, we then form three subgroups based on the third and seventh deciles of the book-to-market ratio (obtained with the December $t-1$ data) to obtain a 'value' portfolio, a 'neutral' portfolio and a 'growth' portfolio. The six portfolios are presented in Table 1.

The six portfolios are constructed every year and are rebalanced in light of changes in the characteristics of the firms. The SMB risk factor is constructed using these six portfolios, whereas the HML risk factor is constructed using four portfolios (the two median portfolios are excluded). The SMB risk factor is the return premium associated with the portfolio of small market capitalization companies versus the portfolio of large market capitalization companies

$$\begin{aligned} SMB = {} & 1/3(\text{Small Value} + \text{Small Neutral} \\ & + \text{Small Growth}) - 1/3(\text{Big Value} \\ & + \text{Big Neutral} + \text{Big Growth}) \end{aligned}$$

The risk factor HML corresponds to the return premium associated with 'value' versus 'growth' portfolios. It is the monthly difference between the average of the returns of portfolios with high book-to-market ratio and portfolios with low book-to-market ratio

$$\begin{aligned} HML = {} & 1/2(\text{Small Value} + \text{Big Value}) \\ & - 1/2(\text{Small Growth} + \text{Big Growth}) \end{aligned}$$

We exclude the momentum factor (UMD) of Carhart (1997). Denoting the momentum of month t by $MOM_{j,t} = R_{j,t-1}/R_{j,t-12}$, we observe that this value is not defined when the return of month $t-12$ is zero. This is because many of the stocks of our sample[8] have several months without transactions: their returns are zero during the months of inactivity, causing computation of this factor to produce many missing values.

Analysing the average returns of the risk factors

The risk factors are the market risk premium $R_M - R_F$, the size risk factor SMB and the growth risk factor HML. Table 2 presents average stock excess returns and the excess returns of the three risk factors for the 90 months of our study.

The risk premiums associated with the three risk factors were expected to be positive most of the time. This is not the case in our sample. For the risk factors $R_M - R_F$, 46% of risk premiums are negative. The proportion of negative returns for HML is 36% and for SMB it is 50%. This high proportion of negative observations for the market's excess returns can be attributed to the poor performance of the BRVM Composite over the period 2001–2003. These years account for 46% of negative observations for $R_M - R_F$ during the study period and can be explained by the high volatility associated with uncertainty during that time (2001–2003 corresponds to the start of the political crisis in Côte d'Ivoire, the country that hosts the stock market and is home to most listed companies). This high proportion of negative returns was observed in other emerging stock markets: for instance, Aksu and Onder (2003) found a proportion of 52% in the Turkish market, and Ben Naceur and Ghazouani (2007) found a proportion of 60% over 5 years on the Tunisian stock market.

The average premiums for the risk factors are 0.5846% for $R_M - R_F$, 0.0025% for SMB and 1.4760% for HML. There is then a big gap between the returns associated with the different risk factors. Although the market seems to reward the HML risk factor more than the other risk factors, the Student t-statistic indicates that none of the premiums for $R_M - R_F$ and SMB are significantly different from zero at the 5% significance level, and that only the

[6] Using book-to-market ratios of December $t-1$ to explain returns realized from July t to June $t+1$ have the advantage of giving companies time to publish their financial statements and giving investors time to react to the figures. This system ensures that financial information was available before the realization of the returns we wish to explain. The law governing financial reporting requires firms to produce quarterly financial statements from the date of their annual meeting: the deadline for holding the annual meeting is 30 June of year $t+1$.

[7] Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/

[8] For the 28 companies in our sample, only three traded stock in every month during the study period.

Table 2. Average monthly returns of the stocks and the three risk factors from July 2001 to December 2008

Year	Month	$R_j - R_F$	$R_M - R_F$	SMB	HML
July 2001–June 2002	July	−0.031502	−0.060450	0.026677	−0.019252
	August	−0.029049	−0.052235	0.020375	0.007146
	September	−0.022528	−0.005065	0.006261	−0.027746
	October	−0.020958	−0.016100	0.008294	−0.025199
	November	−0.017759	−0.011146	−0.016729	−0.008589
	December	0.047358	0.023175	−0.035015	0.122905
	January	0.009490	0.080435	−0.001839	0.000734
	February	−0.021719	−0.046530	0.046746	0.015367
	March	−0.031507	−0.032628	−0.012031	−0.012205
	April	−0.010742	−0.012232	−0.023841	−0.075778
	May	−0.023096	0.004943	−0.022307	−0.022398
	June	−0.021429	−0.003567	−0.025325	−0.012132
July 2002–June 2003	July	−0.023748	−0.034114	0.019071	0.011067
	August	−0.015178	−0.027115	0.019475	−0.017971
	September	−0.003408	−0.007893	0.009498	−0.006985
	October	−0.004997	−0.006588	0.000767	0.002189
	November	0.008765	0.007759	−0.019067	−0.020632
	December	0.049663	0.052807	−0.039477	0.070491
	January	−0.008444	0.029090	0.000478	0.009539
	February	−0.024568	−0.017916	−0.004186	−0.006838
	March	−0.032752	−0.027744	0.019327	−0.030938
	April	−0.021788	−0.043209	0.008795	0.059421
	May	−0.004250	0.008684	−0.020677	−0.001687
	June	−0.019116	−0.014036	0.020108	−0.027710
July 2003–June 2004	July	−0.035778	−0.043343	0.031330	−0.064521
	August	−0.015770	−0.010090	−0.003452	0.049004
	September	0.018452	0.006273	−0.022365	−0.003442
	October	0.005572	0.012997	0.016612	0.048975
	November	−0.011184	0.005411	−0.030155	0.042460
	December	0.042633	0.038863	−0.072712	0.064928
	January	−0.011886	0.047783	0.033472	0.023128
	February	−0.002287	−0.008095	0.019894	0.028956
	March	0.002684	0.016220	−0.001955	0.022597
	April	0.003371	0.024262	−0.026971	0.012650
	May	0.000169	0.007871	0.037310	0.023755
	June	0.000934	0.006853	0.015741	0.014106
July 2004–June 2005	July	−0.017581	−0.010479	0.011718	−0.009114
	August	−0.006647	−0.008304	0.010000	−0.029295
	September	−0.035790	−0.016041	0.011160	0.003796
	October	−0.012455	−0.012156	−0.006122	0.044298
	November	0.020021	0.020191	0.013659	0.016299
	December	0.059483	0.061063	−0.019756	0.019679
	January	−0.025262	0.013408	0.021870	0.007890
	February	−0.038289	−0.023461	−0.013273	−0.069533
	March	0.021236	0.010027	0.009419	0.015689
	April	0.028063	0.010545	−0.000655	0.093169
	May	0.013801	0.096761	−0.014631	0.120367
	June	−0.009732	0.056986	−0.009744	−0.022057
July 2005–June 2006	July	−0.030534	−0.064604	0.007751	−0.015719
	August	−0.022729	−0.018167	0.020980	0.012942
	September	0.000031	−0.002082	−0.022670	0.004176
	October	−0.020999	0.029239	0.019828	−0.033132
	November	0.008521	0.027693	−0.023471	0.040090
	December	0.033715	0.053171	−0.056981	0.003602
	January	0.027620	0.174393	−0.004407	0.001573
	February	−0.024114	0.029357	0.007921	−0.029624
	March	0.019904	0.005729	−0.013809	0.001325

(*continued*)

Table 2. Continued

Year	Month	$R_j - R_F$	$R_M - R_F$	SMB	HML
	April	0.033082	0.021975	−0.082793	0.020027
	May	0.015573	−0.030958	0.111849	0.125800
	June	−0.007938	−0.004641	−0.015297	0.042122
July 2006–June 2007	July	−0.002378	−0.034321	0.040108	0.065489
	August	0.016248	0.008768	0.011982	0.029015
	September	0.010486	0.121654	−0.007307	−0.029158
	October	0.004374	−0.154399	0.062914	−0.110872
	November	0.014518	−0.061498	0.000270	0.012740
	December	−0.011197	−0.061770	0.011903	0.043267
	January	−0.007924	−0.011221	−0.022519	0.012861
	February	0.020504	0.027715	−0.022212	0.033799
	March	0.037873	0.107500	−0.069621	−0.009217
	April	0.033328	0.035005	−0.061014	0.088560
	May	0.030061	0.015308	−0.014094	0.130069
	June	0.074617	0.084824	0.032764	−0.150969
July 2007–June 2008	July	0.054030	0.093944	0.004966	0.000225
	August	0.071263	0.086573	−0.006078	0.051904
	September	0.119889	0.065454	0.033132	0.102266
	October	0.020805	−0.008955	0.065709	0.050195
	November	0.029680	0.023752	−0.018263	0.026837
	December	−0.010922	−0.001284	−0.052740	0.000548
	January	−0.000723	0.031281	−0.015623	−0.027337
	February	0.011037	0.042762	−0.035032	0.004686
	March	0.022593	0.034353	−0.036311	0.025632
	April	0.043970	0.028832	−0.063606	0.033278
	May	0.014054	0.018057	−0.028093	0.116283
	June	0.027898	0.006164	0.118292	0.128727
July 2008–December 2008	July	0.070736	−0.011197	0.001242	0.122581
	August	0.093354	0.025166	0.060473	0.064996
	September	0.065093	−0.061808	0.077312	0.142917
	October	−0.089957	−0.089567	0.009532	−0.072348
	November	−0.130956	−0.153691	0.046325	−0.102734
	December	−0.064047	0.005732	−0.066821	−0.065574
Mean		0.003566	0.005846	0.000025	0.014760
SD (σ)		0.036308	0.049875	0.035647	0.054639
Student-t value		0.926556	1.105704	0.006654	2.548521
Number of negative observations		45	41	45	32
Proportion of negative observations in the sample		50%	46%	50%	36%

Note: The value of the Student-t statistic is calculated by dividing the mean of the monthly returns by $\sigma/(T-1)^{0,5}$.

premium for the HML risk factor is significant at the 5% significance level.

Results of the CAPM estimations

For the empirical examination of their model, Fama and French (1993) considered 100 portfolios of securities sorted by size and book-to-market value. Other studies, such as Bornholt (2007) for the Australian market and Rogers and Securato (2007) for the Brazilian market, used 25 portfolios sorted by quintiles of the same variables for small samples of firms. The reduced number of firms in our sample (28) makes this type of portfolio sorting less appropriate. We use individual stock data to perform our regressions instead. According to Avramov and Chordia (2006), using individual stock data instead of aggregate portfolio data avoids two problems: the loss of information when securities are grouped in portfolios, and biases in the data that are associated with the construction of portfolios.

In the case of individual stock data, we can adopt one of the two approaches: either perform a panel regression, as was done by Ben Naceur and Ghazouani (2007), or perform regressions for each individual stock. Before choosing an approach, we proceed with a Fisher test to detect whether our data has a panel structure. We follow the general test

Table 3. Fisher-statistic values for the specification of a panel model

	F_1	F_2	F_3
CAPM	1.7065	2.7022	0.6979
	(0.001)	(0.000)	(0.875)
FF	4.6693	5.9559	0.6973
	(0.000)	(0.000)	(0.875)

Note: Numbers in parentheses are *p*-values.

procedure proposed by Hsiao (1986). Table 3 presents the value of the Fisher test statistics and their *p*-values in parentheses.

We observe that the *p*-values of the *F*-statistics are largely inferior to the significance level of 1%. Therefore, we reject the null hypothesis that our data has a panel structure and proceed with individual regressions for each stock.

Table 4 presents the estimation results of the CAPM using the Ordinary Least Squares (OLS) method for each stock of the sample. Before interpreting the results, we must check whether the OLS assumptions hold. The statistical tests on the parameters as well as the good properties of the estimators are based on the normality, homoscedasticity and the absence of autocorrelation of the error term assumptions.

The normality of the residuals is tested with the Jarque–Bera (JB) statistic. We reject the normality assumption in almost all residuals, except for only two stocks. Since the Student *t* and the Fisher statistics assume normality for the residuals, we use the Wald statistic to test for the significance of the coefficients.

The absence of autocorrelation of the errors is tested with the Breusch–Godfrey method because the Durbin–Watson statistic assumes normality for the residuals. The autocorrelation test is done for up to order 4 and the statistic follows a chi-square distribution with four degrees of freedom. For the 28 stocks of our sample, 12 have autocorrelated errors at the 5% significance level, indicating that the OLS coefficient estimates of the CAPM for these stocks are biased. There are several techniques to correct for autocorrelation of the residuals obtained by the OLS method, each of which requires introducing new variables in the model. This compromises the CAPM because in the CAPM, the market risk premium is the only element to explain variations in excess stock returns; securities returns with autocorrelated residuals are not explained. Thus, only 16 of the 28 stocks remain to be tested, these stocks are highlighted in grey in the table.

The White heteroscedasticity test shows that the residuals of five regressions are heteroscedastic and that the value of the Fisher statistic for these stocks is superior to the critical value at the 5% level. The violation of homoscedasticity in the error terms does not necessarily bias the parameters estimation. However, the SD of the OLS estimates is not minimal, thus the estimates are no longer converging. The White correction technique is used in this case.

Hence, none of the regressions satisfy the OLS assumptions. Table 5 presents the value of the Wald-statistic for the regressions with nonnormal residuals. For cases with heteroscedasticity problem, the White estimates for the asymptotic covariance matrix allow us to compute the SD of the coefficient estimates. At the 5% significance level, 11 of the 16 remaining stocks satisfy the CAPM. These stocks are highlighted in grey in the table. For the remaining five stocks, either the *p*-value of the intercept is inferior to 5%, which means that the null hypothesis of the constant can be rejected at the 5% level, or the *p*-value of the null hypothesis of beta equals zero is superior to 5%, meaning that their beta is not different from zero at a statistically significant level.

In sum, of the 28 stocks of our initial sample, 11 or 39.29% satisfy the CAPM. The average of their adjusted R^2 is 11.32%. Hence, when CAPM theory holds, the market risk premium would explain an average of 11.32% of the variations in stock excess returns.

It is useful to verify whether adding explanatory risk factors other than the market improves the R^2. In the next section, we test the FF with BRVM stock data.

Estimation results for the Fama–French three-factor model

Table 6 presents results of the estimates of the FF for stocks listed on the BRVM. We observe an average positive beta of 0.3870. Only two stocks have negative beta; the others are positively correlated with the market. Half of the stocks (14) have beta that is nonstatistically null. In other words, in most cases, introducing additional risk factors has improved the significance of the beta. This implies that for most stocks, the market does reward market risk *per se*.

The average coefficient of the *SMB* risk factor is positive (0.0818), much lower than that of the market risk factor. Half (14) of the companies have positive *SMB* coefficients. The average coefficient value of the *HML* risk factor is positive (0.2599). The BRVM is dominated by 'value' stocks, which under-performed during the study period. 21 firms with positive *HML* coefficients can be considered as 'value' stocks, while

Table 4. OLS estimations of the CAPM and validity tests

Stock	Intercept	Beta	JB	Breusch–Godfrey	White test	Adjusted R^2
ABJC	−0.0024004 (1.9419)	0.6763088 (−0.1380)	263.6***	17.170**	13.28**	0.0301932
BICC	−0.002647 (1.9931)	0.3591709 (−0.2941)	52.55***	0.84	1.55	0.0323199
BNBC	0.0040128 (1.9475)	0.2715988 (0.5762)	6.391**	9.032*	2.10	0.0304252
BOAB	−0.000898 (−0.9101)	−0.042718 (−0.3831)	1578***	11.922**	0.30	−0.0019329
CABC	−0.009769 (1.4812)	0.3395862 (−0.8532)	360.1***	25.518***	0.97	0.0132385
CFAC	0.0044969 (0.0065)	0.0008821 (0.6667)	167.6***	21.079***	0.12	−0.0113631
CIEC	−0.0032546 (4.1657)	0.7000502 (−0.3878)	1.5730	12.016**	3.21	0.1552202
FTSC	−0.0199472 (2.4258)	0.6019482 (−1.6096)	340***	3.8090	1.37	0.0520261
NTCL	−0.0060329 (1.1094)	0.1665314 (−0.8048)	453.3***	34.366***	1.10	0.0025873
PALC	0.0065229 (2.9712)	0.7896813 (0.4914)	49.76***	8.617*	0.31	0.0808458
PRSC	0.0088905 (−0.5145)	−0.0902196 (1.0152)	1742***	23.412***	0.57	−0.0083305
SAGC	0.004645 (2.8808)	0.8039739 (0.4223)	27.97***	2.7430	2.5	0.1100939
SDCC	−0.0045751 (2.0711)	0.4159452 (−0.4562)	125.9***	6.0210	6.97**	0.0356456
SDVC	0.010485 (0.8638)	0.1567589 (1.2265)	40.91***	9.728**	0.51	−0.0037469
SEMC	0.0059556 (1.3342)	0.2247077 (0.7080)	148.6***	9.188*	0.81	0.0086888
SGBC	0.003168 (4.4938)	0.8860154 (0.3217)	2.679	4.5540	7.20**	0.177403
SHEC	−0.0028126 (2.6016)	0.6650676 (−0.2203)	101.7***	14.572***	7.21**	0.0608692
SICC	−0.0069753 (−1.4702)	−0.1552214 (−1.3611)	174.8***	2.8730	0.17	0.0130252
SIVC	−0.0021952 (2.3045)	0.3746743 (−0.2704)	38.57***	2.960	5.88*	0.0461968
SLBC	0.0027275 (2.4727)	0.5632089 (0.2398)	1129***	3.342	1.01	0.0543411
SMBC	0.0052802 (1.0240)	0.1988115 (0.5446)	436.6***	14.521***	0.60	0.0005454
SNTS	0.0091078 (9.010)	1.023235 (1.6059)	36.93***	2.880	24.95***	0.4739326
SOGC	0.0079393 (3.9115)	0.9077048 (0.6850)	20.94***	2.334	1.08	0.1384277
SPHC	0.0178514 (2.2676)	0.5730703 (1.4144)	21.53***	6.681	0.57	0.0444681
SRIC	−0.0037235 (−0.3913)	−0.0190338 (−1.5261)	2089***	11.420**	0.74	−0.0097173
STBC	−0.0045471 (2.6190)	0.4155177 (−0.5739)	11.67**	15.329***	4.00	0.0617673
TATC	0.0085014 (1.7236)	0.3657635 (1.0166)	9.822***	6.284	0.96	0.0323236
TTRC	−0.0063944 (1.6438)	0.4079926 (−0.5159)	65***	8.956*	3.83	0.0187672

Notes: Numbers in parentheses are Student-t statistics.
***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

Table 5. Values of the Wald statistic for linear restriction

Stock	Wald statistic for the intercept	Wald statistic p-value for the intercept	Wald statistic for the beta	Wald statistic p-value for the beta
BICC	0.09	0.7694	3.97	0.0493
BNBC	0.33	0.5660	3.79	0.0547
FTSC	2.59	0.1111	5.88	0.0173
PALC	0.24	0.6243	8.83	0.0038
SAGC	0.18	0.6743	8.30	0.0056
SDCC	0.21	0.6494	4.29	0.0413
SEMC	0.50	0.4808	1.78	0.1856
SGBC	0.7484	0.10	20.19	0.0000
SICC	1.85	0.1770	2.16	0.1451
SIVC	0.07	0.7875	5.31	0.0235
SLBC	0.06	0.8111	6.11	0.0153
SNTS	2.58	0.1119	81.18	0.0000
SOGC	0.47	0.4951	15.30	0.0002
SPHC	2.00	0.1608	5.14	0.0258
TATC	1.03	0.3136	2.97	0.0901
TTRC	0.27	0.6072	2.70	0.1038

the other seven can be characterized as 'growth' stocks. Finally, the average adjusted R^2 for the whole sample is 14.90%, which is superior to the 5.85% obtained with the CAPM.

After this naive interpretation of the results, we turn our attention to the results of the various validation tests. For 25 stocks, the residuals are not distributed normally. For 12 stocks, the homoscedasticity hypothesis is rejected using the White test. For the autocorrelation of the residuals, as in the CAPM section above, regressions with autocorrelated residuals are excluded from the analysis, which includes 11 stocks. For these stocks, we can conclude that the FF is inappropriate for explaining returns, since autocorrelated residuals mean either that at least one important explanatory variable is missing or that the model is misspecified. However, contrary to when the CAPM was examined previously, the residuals of SDV CI (SDVC) and SARI CI (SRIC) are no longer autocorrelated. We then conclude that the autocorrelation detected with the CAPM estimation is indeed the result of the absence of important explanatory variables. We are then left with 17 stocks to analyse. These stocks are highlighted in grey in the table.

Table 7 presents the Wald-test results for the significance of the coefficients. We find that the intercept is significant for three stocks at the 5% level. These stocks therefore reject one of the hypotheses of the FF: that the constant α is null. Testing the joint nullity of the coefficients other than the constant (i.e. $H_0 : b_j = s_j = h_j = 0$), we would like to test whether the stocks' returns are generated from a FF-type pricing model. Otherwise, a model with intercept only will be preferred. Among the 14 remaining stocks, eight stocks reject the null hypothesis, meaning that at least one of the three coefficients is not null. Furthermore, analysing the Wald-statistic values of the individual coefficients, we find that for two stocks, at least one of the three coefficients differs from zero. This yields 10 significant models. Of the 17 remaining stocks, we find 10 stocks to be globally significant.

The 10 stocks retained here are those with a nonsignificant constant and those for which the coefficient of at least one of the three risk factors is significant. These stocks are highlighted in grey in Table 7. For these 10 stocks, we also test the joint nullity of the coefficients of the two additional factors (SMB and HML) (i.e. H_0: $s_j = h_j = 0$) to gauge which model – the FF or the CAPM – is the most appropriate for explaining stock returns. At the 5% significance level, we accept the null hypothesis of a simultaneous nonsignificant coefficient for SMB and HML for four stocks. At the 10% significance level, only TRITURAF CI (TTRC) accepts this hypothesis. Thus, most stocks satisfying these properties reject a CAPM-type specification for a more general three-factor FF.

Finally, of the 28 stocks initially considered, 10 or 35.71% satisfy the FF. Their average adjusted R^2 is 20.40%.

III. Conclusion

Our objective in this article was to examine the empirical validity of and compare asset pricing models for stocks listed on the BRVM, the common stock market of the WAEMU. We used two

Table 6. OLS coefficient estimates for the three-factor Fama–French model and validity tests

Stock	Intercept	$R_M - R_F$	SMB	HML	JB	Breusch–Godfrey	White test	Adjusted R^2
ABJC	−0.0222175	0.8829303	1.492487	1.217663	71.72***	19.462***	26.67***	0.3284634
	(−1.4943)	(2.7516)	(3.6488)	(4.6786)				
BICC	−0.0086451	0.190847	−0.2360767	0.5096262	30.84***	2.382	13.53	0.1239093
	(−0.9828)	(1.0053)	(−0.9755)	(3.3096)				
BNBC	0.0011667	0.353815	0.3708862	0.142772	10.71**	10.112**	8.91	0.0710082
	(0.1666)	(2.3409)	(1.9250)	(1.1646)				
BOAB	−0.0007791	−0.0682401	−0.0812966	0.0075366	1820***	10.341**	2.98	−0.0076882
	(−0.3226)	(−1.3093)	(−1.2237)	(0.1783)				
CABC	−0.0147801	0.5928478	0.9762852	0.1850761	237.8***	16.758***	7.56	0.115827
	(−1.3276)	(2.4673)	(3.1874)	(0.9497)				
CFAC	0.0000276	0.1325309	0.5899897	0.2226488	84.33***	12.660**	15.45*	0.1407564
	(0.0043)	(0.9616)	(3.3580)	(1.9916)				
CIEC	−0.0098244	0.4315807	−0.5091457	0.6095902	1.238	17.618***	12.21	0.3201115
	(−1.2703)	(2.5855)	(−2.3928)	(4.5024)				
FTSC	−0.0241302	0.5007674	−0.1163511	0.3455074	285.7***	3.698	23.21***	0.0566025
	(−1.9001)	(1.8270)	(−0.3330)	(1.5542)				
NTLC	−0.002223	0.0730062	−0.4472296	−0.2012272	147.9***	32.423***	34.54***	0.0695656
	(−0.2989)	(0.4548)	(−2.1857)	(−1.5456)				
PALC	−0.0055854	0.5461429	−0.1897918	0.9699573	30.8***	8.369*	32.19***	0.2360681
	(−0.4493)	(2.0358)	(−0.5550)	(4.4577)				
PRSC	0.0026647	0.0189783	0.600823	0.3554834	1237***	11.375**	15.10*	0.1191335
	(0.3169)	(0.1046)	(2.5974)	(2.4152)				
SAGC	−0.0011231	0.5866882	−0.2017609	0.7579674	25.93***	3.371	4.66	0.2325008
	(−0.1081)	(2.0616)	(−0.6282)	(3.3360)				
SDCC	−0.0074414	0.5095821	0.4058034	0.1371598	118.6***	8.136*	18.59**	0.046991
	(−0.7266)	(2.3053)	(1.44019)	(0.7650)				
SDVC	0.0068018	0.0701919	−0.0158635	0.4602319	61.11***	9.247*	5.22	0.0567971
	(0.8073)	(0.3495)	(−0.0588)	(2.5078)				
SEMC	0.0038344	0.2986767	0.3142391	0.0986523	184.6***	7.170	4.26	0.0142081
	(0.4450)	(1.6061)	(1.3257)	(0.6541)				
SGBC	−0.0036503	0.4900001	−0.8781506	0.7043782	0.8695	2.462	19.70**	0.3743546
	(−0.4138)	(2.5738)	(−3.6184)	(4.5615)				
SHEC	−0.011538	0.5891402	0.1598818	0.6381189	50.49***	19.885***	20.37**	0.1314704
	(−0.9149)	(2.1644)	(0.4608)	(2.8904)				
SICC	−0.0081517	−0.1464266	0.0816259	0.0719798	158.9***	2.450	2.99	0.0023832
	(−1.5369)	(−1.2334)	(0.5595)	(0.7714)				
SIVC	−0.0029338	0.4998321	0.4055676	−0.0263897	27.44***	2.816	29.40***	0.0587293
	(−0.3541)	(2.7951)	(1.7791)	(−0.1819)				
SLBC	0.0117669	0.8358901	0.4124159	−0.7796416	526.1***	2.589	27.48***	0.1979988
	(1.0935)	(3.5992)	(1.3930)	(−4.1389)				
SMBC	0.0049459	0.251282	0.1711188	−0.0093923	434.9***	14.745***	2.86	−0.018149
	(0.4920)	(1.1582)	(0.6187)	(−0.0534)				
SNTS	0.0125002	1.059947	−0.0407319	−0.2524904	20.27***	2.013	44.41***	0.5015689
	(2.2042)	(8.6601)	(−0.2611)	(−2.5434)				
SOGC	−0.0017752	0.7440408	−0.0577481	0.7588055	5.846*	1.559	10.88	0.2525133
	(−0.1601)	(3.1089)	(−0.1893)	(3.9091)				
SPHC	0.0097457	0.1574774	−0.8795124	0.8036473	12.53***	7.370	4.53	0.204603
	(0.8239)	(0.6168)	(−2.7026)	(3.8811)				
SRIC	−0.005161	0.0097465	0.1490436	0.0788541	756.1***	7.985*	34.07***	0.077353
	(−2.1552)	(0.1894)	(2.2705)	(1.8892)				
STBC	−0.0026483	0.267076	−0.5262747	−0.0380611	15.54***	11.270**	7.80	0.1043776
	(−0.3330)	(1.5561)	(−2.4055)	(−0.2734)				
TATC	0.0147508	0.3186253	−0.5285999	−0.6253353	11.44**	6.348	4.38	0.2845467
	(2.0158)	(1.5903)	(−2.3376)	(−3.9093)				
TTRC	−0.0104476	0.6397904	0.8699518	0.1332317	68***	3.975	28.19***	0.0770993
	(−0.8461)	(2.4007)	(2.5607)	(0.6164)				

Notes: Numbers in parentheses are Student-*t* statistics.
***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

Table 7. Wald joint nullity tests for the remaining stocks

Stock	W-stat. $\alpha_j=0$	W-stat. $b_j=0$	W-stat. $s_j=0$	W-stat. $h_j=0$	W-stat. $b_j=s_j=h_j=0$	W-stat. $s_j=h_j=0$
BICC	1.14	0.88	1.00	5.86	4.84	3.03
	(0.2893)	(0.3499)	(0.3200)	(0.0175)	(0.0037)	(0.0533)
FTSC	4.71	2.62	0.10	2.42	2.68	1.69
	(0.0326)	(0.1093)	(0.7502)	(0.1235)	(0.0521)	(0.1912)
PALC	0.29	6.65	0.14	14.83	7.51	7.43
	(0.5898)	(0.0116)	(0.7122)	(0.0002)	(0.0002)	(0.0010)
SAGC	0.01	3.82	0.42	10.25	5.01	5.04
	(0.9140)	(0.0554)	(0.5186)	(0.0022)	(0.0037)	(0.0096)
SDCC	0.64	3.79	1.70	0.36	2.25	1.81
	(0.4270)	(0.0546)	(0.1951)	(0.5498)	(0.0878)	(0.1701)
SDVC	0.78	0.29	0.00	5.08	2.13	2.84
	(0.3813)	(0.5923)	(0.9613)	(0.0274)	(0.1042)	(0.0652)
SEMC	0.18	3.34	2.51	0.58	1.69	2.10
	(0.6731)	(0.0709)	(0.1164)	(0.4468)	(0.1742)	(0.1288)
SGBC	0.16	5.07	8.17	15.37	9.86	10.36
	(0.6882)	(0.0267)	(0.0053)	(0.0002)	(0.0000)	(0.0001)
SICC	2.49	2.06	0.39	1.30	1.56	0.65
	(0.1182)	(0.1545)	(0.5358)	(0.2581)	(0.2043)	(0.5235)
SIVC	0.12	3.21	2.27	0.01	1.96	1.84
	(0.7251)	(0.0765)	(0.1351)	(0.9062)	(0.1253)	(0.1652)
SLBC	2.04	7.84	1.33	4.93	3.27	2.45
	(0.1570)	(0.0063)	(0.2527)	(0.0290)	(0.0249)	(0.0918)
SNTS	3.95	24.76	0.06	4.34	10.50	2.19
	(0.0500)	(0.0000)	(0.8135)	(0.0402)	(0.0000)	(0.1176)
SOGC	0.03	10.29	0.03	10.24	10.02	5.78
	(0.8656)	(0.0019)	(0.8663)	(0.0019)	(0.0000)	(0.0044)
SPHC	0.68	0.38	8.15	16.96	7.06	9.19
	(0.4135)	(0.5410)	(0.0054)	(0.0001)	(0.0003)	(0.0002)
SRIC	6.75	0.02	1.34	1.76	0.78	0.97
	(0.0110)	(0.8843)	(0.2504)	(0.1884)	(0.5109)	(0.3841)
TATC	3.82	5.16	9.77	30.58	16.67	18.52
	(0.0553)	(0.0268)	(0.0027)	(0.0000)	(0.0000)	(0.0000)
TTRC	1.16	4.37	2.95	0.37	1.56	1.46
	(0.2851)	(0.0393)	(0.0894)	(0.5423)	(0.2052)	(0.2383)

Note: Numbers in parentheses are Wald statistic p-values.

well-known asset-pricing models: the CAPM and the three-factor Fama–French (1992) model.

Given the heterogeneity of the stocks in our sample, we adopted the OLS regression method for each stock. We found that only 11 of the 28 stocks (39.29%) satisfied the CAPM. When the CAPM held, the market premium explained on average 11.32% of the variations of stock returns. Using the three-factor Fama–French model improved the results noticeably: 10 of the 28 stocks (35.71%) satisfied this model for an average adjusted R^2 of 20.40%. From this, it is clear that the three-factor Fama–French model is more appropriate for explaining variations in returns in the BRVM than the CAPM model. But the Fama–French model has limitations, since it failed to explain the variations in returns of more than 60% of the stocks listed on this market. To resolve this difficulty, several research avenues can be explored: for example, using another alternative conditional CAPM pricing model like Jagannathan and Wang's (1996) three-factor model or extensions of earlier factor models.

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Appendix: Names and Tickers of BRVM Stocks Included in the Study Sample

	Company name	Ticker
1	ABIDJAN CATERING CI	ABJC
2	BICI CI	BICC
3	BERNABE CI	BNBC
4	BOA BENIN	BOAB
5	SICABLE CI	CABC
6	CFAO CI	CFAC
7	CIE CI	CIEC
8	FILTISAC CI	FTSC
9	NESTLE CI	NTCL
10	PALM CI	PALC
11	PEYRISSAC CI	PRSC
12	SAGA CI	SAGC
13	SODE CI	SDCC
14	SDV CI	SDVC
15	SIEM CI	SEMC
16	SGBCI	SGBC
17	SHELL CI	SHEC
18	SICOR CI	SICC
19	SIVOA CI	SIVC
20	SOLIBRA CI	SLBC
21	SMB CI	SMBC
22	SONATEL SN	SNTS
23	SOGB CI	SOGC
24	SAPH CI	SPHC
25	SARI CI	SRIC
26	SITAB CI	STBC
27	TOTAL CI	TATC
28	TRITURAF CI	TTRC