Scientific Research Publishing

Modern Economy, 2025, 16(11), 1802-1826
https://www.scirp.org/journal/me
ISSN Online: 2152-7261
ISSN Print: 2152-7245

Detection of Calendar Effects, Measurement of Investor Sentiment and Analysis of Their Effects on the Volatility of BRVM Returns

Djahoué Mangblé Gérald

Alassane Ouattara University of Bouaké, Bouaké, Ivory Coast
Email: Djahoue225@gmail.com

How to cite this paper: Gérald, D. M. (2025). Detection of Calendar Effects, Measurement of Investor Sentiment and Analysis of Their Effects on the Volatility of BRVM Returns. *Modern Economy, 16,* 1802-1826.
https://doi.org/10.4236/me.2025.1611083

Received: May 23, 2025
Accepted: November 10, 2025
Published: November 13, 2025

Abstract

Our study focused on daily data from the Regional Stock Exchange (BRVM) covering the period from 4 January 2014 to 26 February 2025. We selected five indices, including the two main indices and the three sector indices with the highest number of listed companies. Our goal was to detect the existence of calendar anomalies and analyse their combined effects with investor sentiment on stock market returns. To do this, we used two different approaches (linear modelling and the application of a binomial Logit model) on dummy variables for days of the week and the investor sentiment indicator. Using the linear regression approach, we tested the effect of investor sentiment and the days of the week on BRVM returns. The binomial Logit regression approach was then used to determine the effect of investor sentiment on market direction. Our various results showed that investor sentiment played an important role in the evolution of BRVM stock market returns. The results also indicate that there is no consensus on the effect of calendar anomalies, mainly those of the days of the week, on BRVM returns. Indeed, weekday anomalies vary according to the different indices. We also found that there was a positive and significant effect of the month (January effect) on the stock market. We justified this result through the literature as the result of strategies developed by investors and various market players to either avoid high taxation or as an opportunity to take advantage of year-end bonuses to acquire more assets in order to expand and diversify their stock portfolios.

Keywords

Investor Sentiment, Calendar Anomalies, Stock Market Volatility, BRVM

1. Introduction

Several theoretical and empirical debates have long been raging in the world of finance in general and the stock markets in particular. However, one of the most discussed issues in the financial literature concerns whether or not there has been a paradigm shift (Gouider et al., 2015). That is, whether we should continue to analyse stock prices on the assumption that the economic agents acting in these markets are rational beings. This would lead to the conclusion that stock markets are efficient. Or whether we should start to take into account the (often subjective) factors that significantly influence stock price behaviour. It is in this context that our study positions itself as an extension of the existing literature by analysing the presence of calendar anomalies and investor sentiment, as well as their likely effects on BRVM returns.

Indeed, the literature clearly shows that there is no compromise on the existence of calendar anomalies in stock markets. It also argues that, even when they do exist, their influence on market direction is subject to various interpretations (Da et al., 2015). With regard to investor sentiment, we believe that it can have a profound impact on the economy as a whole. Indeed, according to Lutz (2016), the proliferation of speculative bubbles (the 2008 global financial crisis and others) has forced policymakers to closely monitor measures of investor sentiment. It is therefore essential for researchers to develop a deep understanding of the effects and drivers of this decision-making indicator.

In short, our motivation for this topic is twofold: first, we want to provide a better understanding of how stock markets work, mainly in terms of price formation and prediction on these markets. Second, we aim to place the psychology of market participants back at the centre of the economic debate with a view to improving the quality of stock market forecasting. We cannot deny the importance of this topic for financial literature, in that its originality and contribution add a special dimension to the renewed debate on emerging stock markets. Throughout this work, we attempt to contribute to economic thinking by reconciling neoclassical finance theory and behavioural finance theory in order to reveal the importance of taking into account the heterogeneous and psychological dimension of investors in the formation and forecasting of stock market prices.

Financial market data are unique in their functioning and their dynamic, nonlinear, non-stationary, non-parametric and noisy nature (Abu-Mostafa & Atiya, 1996). As a result, investors should not be denied expertise in understanding this behaviour. Thus, for Zhong and Enke (2019), the complexity of stock market data is fundamentally a function of many highly interdependent factors, including economic, political and psychological variables, as well as variables specific to each company or investor. Faced with all these problems, investors and researchers have, over the years, taken an interest in developing and proposing tests of models adapted to stock market behaviour in order to facilitate their analyses (Liu, 2014).

Economic literature argues that there are two main methodological approaches to analysing financial markets (Nguyen et al., 2015; Park & Irwin, 2007). On the one hand, we find the neoclassical approach to the stock market pioneered by

Fama (1965; 1995), whose conclusions are increasingly being challenged by proponents of behavioural finance (Kahneman & Smith (2002); Shiller (2003); Thaler and Benartzi (2004); Nivoix and Boulerne, (2020); Aleknevičienė et al., (2021); etc.) According to Arévalo et al. (2017), in practice, when economists construct a framework for studying financial markets, they are faced with a fundamental choice between a set of assumptions about investors' judgements, preferences and decisions. This is in line with the conclusions of Shefrin (2005), who believes that the paradigmatic debate on stock markets thus focuses primarily on the thorny question of whether these assumptions should be based on the neoclassical functioning of the market or on the behavioural nature of investors.

Traditionally, finance has adopted the neoclassical analytical framework of microeconomics (Barberis & Thaler, 2003). In this framework, financial decision-makers have preferences regarding uncertain wealth distributions. They use (mathematical) techniques to make appropriate statistical judgements based on the data available to them. The main idea underlying this theory is based on the fact that investors and actors operating in the markets are perfectly rational (Fama, 1965). In other words, these agents always act in accordance with the information available to them. More clearly, the neoclassical conception of finance suggests that economic agents have the necessary cognitive capacity to perfectly process the information available to them in order to make decisions that maximise their satisfaction (Thaler & Benartzi, 2004).

To this end, there are a number of pillars on which these theorists base their analyses:

- Fama's efficient market hypothesis (EMH) (1965, 1970).
- Factor models such as the Capital Asset Pricing Model (CAPM).
- Black et al.'s option pricing theory (1973).
- Markowitz's mean-variance efficient portfolio theory (1952).

However, since the 1980s, several studies have begun to criticise the conclusions of neoclassical financial analyses. There are conclusions that, despite Fama's attempts at a response (1970), anomalies have been discovered and persist (Damasio, 1994; Hirshleifer & Shumway, 2003; etc.). Not only was neoclassical theory initially unable to explain these anomalies, but more importantly, it did not propose any method of analysis that could potentially avoid them (Gouider et al., 2015).

Thus, according to behavioural economists, the main debate among financial economists today should focus on the paradigm shift rather than on any development and explanation of efficiency. The basis of the debate on the paradigm shift in finance involves the way in which economic agents make their investment decisions (Shefrin, 2008). According to Shefrin, not only are investors not always and completely rational, but they most often act with what is known as "[1]". As a

[1]In 1947, Herbert Simon published a book entitled Administrative Behaviour, in which he first developed the concept ***of bounded rationality,*** according to which individuals can only have imperfect knowledge of constraints and possible choices. Herbert Simon highlights that individuals faced with this imperfect information make choices that are not optimal but merely seek to achieve a certain level of aspiration or requirement. Rationality is therefore no longer absolute and objective but is marked by subjectivity and relativity.

result, markets do not always, or even ever, function efficiently.

Unlike the traditional paradigm, which considers investors to be completely rational, behavioural finance offers an alternative paradigm with a broader and more realistic framework (Gouider et al., 2015). Behavioural finance focuses on how psychological and emotional factors influence investors' decisions. It argues that, when making decisions, investors generally try to rely not only on the information available to them, but also on their experiences. According to behavioural finance, experience represents all situations (opportunities, profits, losses, fears, etc.) that have been similarly experienced or heard about (the experiences of others).

[2]Thus, according to Bernstein (2007), repeated examples of irrationality, inconsistency and incompetence are increasingly being revealed in financial analyses. This is particularly true in the way human beings make choices and decisions when faced with uncertainty. Shiller (2000) asserts that economic agents generally make observations, process data and arrive at judgements. In financial matters, these judgements and decisions relate to the composition of individual portfolios, the range of securities offered on the market, the nature of earnings forecasts and the way in which securities evolve. Proponents of behavioural finance theory have thus built their arguments around a number of pricing pillars. Unlike neoclassical finance theorists, behavioural economists have based their reasoning on psychological, emotional and event-driven pillars. Behavioural finance builds its arguments around the following pillars:

- ✓ The heuristics of Tversky and Kahneman (1974) and Shiller (2000).
- ✓ Cognitive and/or emotional biases according to Hirshleifer and Shumway (2003).
- ✓ Tversky and Kahneman's (1974) prospect theory.
- ✓ Thaler's (1999) theory of mental accounting.
- ✓ Odean's (1998) theory of overconfidence.

Thus, despite strong evidence (EMH, portfolio diversification theory, etc.) that stock markets are efficient, anomalies exist. While the existence of these anomalies is accepted, the question of whether investors can exploit them is subject to debate. A number of researchers, such as Tversky and Kahneman, (2000) and Hirshleifer and Shumway (2003), have studied behavioural biases caused by the overreaction or underreaction of the investing public to new information. In particular, they have examined how these biases can influence prices despite the compensatory actions of rational arbitrageurs. According to Hirshleifer and Shumway (2003), there are several behavioural biases that regularly influence investors' decisions. The author believes that these biases can be grouped into two main categories: impulsive behaviour (emotional biases) and errors of judgement or assessment (cognitive biases[3]).

---

[2]The message from Keynes (1923, 1936) and Knight (1921) is clear: uncertainty reigns supreme and any simplification is dangerous. There is no magic tool that can capture the full complexity of an uncertain world.

[3]A cognitive bias is a thought process that causes a deviation in judgement. The term bias refers to a systematic deviation from logical and rational thinking in relation to reality. In general, cognitive biases lead the subject to attach different levels of importance to facts of the same nature. These biases are most often identified when paradoxes appear in reasoning.

Several research findings in economics and psychology in particular (Damasio, 1994; Hirshleifer & Shumway, 2003, etc.) have shown that, in reality, the deficiency or absence of emotions affects various decision-making processes. According to these authors, when an investor has a positive feeling about an asset, this will have an impact on the expected return on that asset. Gibbons and Hess (1981) highlight the Monday effect (weekday effect). According to these authors, asset prices tend to rise on Fridays at the close of trading and then fall sharply on the following Mondays, and vice versa, depending on whether we are looking at the American or European markets. Indeed, proponents of behavioural finance argue that there are unfavourable factors that accompany each new working week. For example, listed companies tend to release negative information only on Friday evenings, just after the close of trading. This is supported by the fact that investors tend to sell all their negative shares on Friday afternoons to avoid potential slippage over the weekend.

More clearly, the days of the week indicate that stock market returns are distributed unevenly. This is further evidence against the efficient market hypothesis (EMH). These anomalies are the result of psychological biases and strategic motivations (Shiller, 2003). Studies by Cross (1973), French (1980), Alexakis and Xanthakis (1995), Pena (1995), Kling and Gao (2008), and others have examined the effect of the days of the week on global financial markets. First, Jaffe and Westerfield (1985) studied the presence of the day-of-the-week effect in four countries (Australia, Canada, Japan and the United Kingdom) and observed that the lowest average returns occurred on Tuesdays for Australia and Japan during various periods between 1950 and 1983. This conclusion contrasts with that of Alberg et al. (2008), who showed that Tuesday had the highest returns compared to other days of the week in their study of the Tel Aviv stock market in Israel. They justify this result by the fact that in Israel, the first trading day is Tuesday, unlike most global stock markets. Khan et al. (2017) reached the same conclusions as Alberg et al. (2008) in their research on the effect of the day of the week on the Karachi stock exchange. Their results indicate a positive and highly significant impact of the day effect (Tuesday) on daily stock market returns. They therefore conclude that, apart from Friday, which is considered the most profitable day of the week according to theory, certain stock markets, depending on their specific characteristics, showed Tuesday to be the most profitable day of the week.

The poor profitability of Mondays had already been observed by French (1980), who argued that Monday's profitability was statistically and significantly negative compared to other days of the week. He also found that Tuesdays had zero profitability, while Fridays had positive profitability. For more details on the Monday effect on stock market returns, see (Dicle & Levendis, 2014; Olson et al., 2015; Zhang et al., 2017; Nivoix & Boulerne, 2020).

In addition to the days of the week, the months of the year also cause anomalies in stock market returns. The January effect or end-of-month effect is another cognitive bias that has been widely studied in the world of finance. It is named after the phenomenon whereby the average monthly return of small companies is always higher than that of large companies, mainly in January. This phenomenon not only contradicts the conclusions of the efficient market hypothesis, but more importantly, it refutes all the arguments developed by Fama et al. (1970). The study by Michael et al. (1976) revealed that from 1904 to 1974, average returns in January for small companies were around 3.5%, while their returns for the other months of the year were closer to 0.5%. This suggests that the monthly performance of small-cap companies follows a relatively consistent pattern, contrary to what proponents of neoclassical theory predict. The most plausible and intuitive explanations for the January effect are generally based on taxation.

Among the most notable studies on the January effect is that of Keim (1983), who showed that stock market returns are higher in January than in other months of the year. He argues that this is because investors generally decide to reduce their taxes at the end of the year. According to Keim (1983), the January effect is related to an oth omity (size effect) also identified in the stock markets. The author found that, particularly in January, the securities of companies with low market capitalisation (small size) consistently yield higher returns than the securities of large companies (large size). He then indicates that the two anomalies (January effect and size effect) are closely related. This thesis thus confirms the conclusions of Michael et al. (1976) and Rozeff and Kinney Jr. (1976). But it is also shared by several other authors in the financial literature, including Barney (2005). He conducted research on the January effect over the period from 1972 to 2002. He found that Russell 2000 Index stocks (small-cap stocks) outperformed Russell 1000 Index stocks (large-cap stocks) by 0.82% in January. For more details on the validity of the January effect on returns in different stock markets, see (Gultekin & Gultekin, 1983; Bhardwaj & Brooks, 1992; Eleswarapu & Reinganum, 1993; Sewraj et al., 2019; Al-smadi et al., 2017; Jebran & Chen, 2017;…).

Financial literature also places particular emphasis on investor sentiment as a profound source of stock market anomalies. Indeed, theorists agree that sentiment can be defined as the set of expectations that are not justified by investors' economic fundamentals (Lemmon & Portniaguina, 2006). More clearly, investor sentiment represents the level of optimism or pessimism beyond what can be explained by fundamental indicators. According to Shefrin (2005), the term "sentiment" in finance is synonymous with "error". Thus, when proponents of behavioural finance refer to the term "sentiment", they are alluding to the aggregate errors of investors that are reflected in stock price movements.

The consideration of investor behaviour or sentiment in financial analysis has attracted particular attention from researchers (Gong et al., 2016; PH & Rishad, 2020;…). Most existing studies on the consideration of investor behaviour in financial analysis have clearly emphasised how investors' emotions affect and guide their investment decisions [Stambaugh et al., 2012; Da et al., 2015]. However, the real difficulty lies in how to capture investor psychology (sentiment) as a "**viable**" variable in the stock markets (Hong & Stein, 2007). Various macroeconomic and financial variables have been used as proxies for investor sentiment [Rapach & Zhou, 2013; Gebka, 2013; Lutz, 2016; etc.].

The article by Edmans et al. (2007) highlights in detail the co-movements between sports results and stock market fluctuations through two major conclusions. First, they show that World Cup match results have statistically significant effects on national stock market returns. They show that the loss of a national team in the knockout stage of the World Cup produces an abnormal stock market return (of -49 basis points) the day after the match. Secondly, they argue that the effects of losses found were not only stronger for low-return stock markets and the most important sports (football, basketball, etc.). The key finding of their analysis is that these results remain robust even when methodological changes are taken into account. However, in a study, Fung et al. (2015) tend to demonstrate that the results of professional football matches influence investor sentiment, which in turn determines the evolution of stock market returns. Using several methods of analysis on three major Turkish football clubs, these authors prove that sports results have a significant impact on stock market volatility. They show that the effect of these results was more pronounced on the returns of small companies or low-yield companies. They first validated the first two conclusions of Edmans et al. (2007). They then showed that the change in methodology (the use of a dynamic panel model) cancelled out the significant effects found by Edmans et al. (2007).

In the macroeconomic context, Sayim et al. (2013) found that the influence of investor sentiment varies from one industry to another. In their study, they found that the effect of investor sentiment is more reflected in the performance indices for the information industry than for the transport industry. Shu and Chang (2015), starting from the classic basic model of Lucas (1978), constructed a simple general equilibrium model (MEGS). Their objective was to determine the importance of economic agents' psychology on their time preferences and risk aversion. Lutz (2016) draws on a FAVAR model proposed by Bernanke et al. (2005) and Boivin et al. (2005) to examine the relationship between monetary policy and investor sentiment. He does this through conventional and unconventional monetary policy regimes. He finds that during conventional periods, a surprise cut in the federal funds rate leads to a sharp increase in investor sentiment.

Similarly, when the federal funds rate is at its lowest level, the research results indicate that unconventional expansionary shocks in monetary policy also have a significant and positive impact on investor sentiment. Several empirical results have shown that investor sentiment can explain stock market volatility (Brown, 1999; Wen et al., 2014a & 2014b; Gong et al., 2016;…). Some of these researchers argue that although investor sentiment cannot necessarily predict future market trends, it nevertheless provides a better explanation for fluctuations. They also show that the influence of investor sentiment most often depends on the quality of the market (emerging, developed, etc.) and the type of investor (local, international, etc.) in these markets.

2. Measures of Investor Sentiment and Calendar Anomalies

This part of our study describes and discusses the different methods of measuring investor sentiment and calendar effects found in the financial literature.

2.1. Measures of Investor Sentiment

Investor sentiment cannot be directly observed due to its subjective and individual nature. As such, various methods have been used in the literature to measure it. However, these different measures can be grouped into three main categories: **direct** measures, **indirect** measures and **exogenous** measures of investor sentiment.

2.1.1. Direct Measurement of Investor Sentiment

The direct method of measuring investor sentiment generally uses opinion polls. These are essentially investor surveys and economic surveys. This method has been the subject of numerous empirical studies in the financial literature. Examples include the surveys conducted by the American Association of Individual Investors by Brown (1999) and by Fisher and Statman (2000). There are also the surveys conducted by Investors Intelligence, carried out by Lee et al. (2002) and Brown and Cliff (2004). The problem with this method is that it has limitations[4] and is only experimental and limited in scope.

2.1.2. Exogenous Measurement of Investor Sentiment

Exogenous measures are external indicators not directly associated with the economy. These measures have also been analysed by several researchers, including Hirshleifer and Shumway (2003) using the sunshine index. Furthermore, Krivelyova and Robboti (2003) measured investor sentiment using geomagnetic storms. Other researchers, such as Yuan et al. (2005) and Edmans et al. (2007), used lunar cycles and sports results, respectively, to test the effect of investor sentiment. However, the literature argues that there is no consensus[5] on the impact of external factors on investor psychology (sentiment).

2.2. Indirect Measurement of Investor Sentiment

Unlike direct and exogenous methods, market-related proxies, which constitute the third method, have the advantage of representing the mood of the economy as a whole. They can be easily generalised and are often available from the most authentic sources (Naik & Padhi, 2016). However, there is no specific number of

[4]The direct method of detecting investor sentiment normally seems to be the most appropriate, as it involves direct contact with those concerned. However, it has many limitations and drawbacks, including:

- The probability of errors during data collection and processing, as investigators neglect the different levels of optimism and pessimism among respondents.
- The representativeness of the population surveyed, which subsequently limits the scope for generalising the results.
- Unavailability, etc.

[5]Indeed, as exogenous phenomena are random, it is difficult to determine their exact effect on individual behaviour. The interpretation of lunar cycles, for example, differs from one continent to another, from one society to another and, above all, from one people to another.

factors to represent implicit market-related proxies. As a result, a plethora of proxies based on observed market outcomes have been used in the literature as indicators of investor sentiment and confidence.

The following section will focus on describing and justifying the different variables chosen. Financial theory argues that the construction of the investor sentiment indicator must be done carefully and explicitly. The sentiment index must reflect reality in the sense that it must be constructed solely from variables of psychological origin.

3. Data Sources and Market Description

We use daily data from the BRVM for the period from 4 January 2014 to 26 February 2025, representing 2791 observations. This data is extracted from the Official Market Bulletin (BOC), which summarises statistics relating to the BRVM 10, BRVM Composite and sector indices, as well as trading volumes, among other things, at the end of each trading session.

The BRVM is a stock market common to the eight countries of the West African Economic and Monetary Union (UEMOA), with 46 companies listed. It tracks two main indices: the BRVM 10, which tracks the 10 most liquid companies on the market, and the BRVM Composite, which tracks all listed companies. We wanted to analyse not only the influence of anomalies on the main indices, but also the effect this could have on sector indices. The choice, which is purely operational, fell on the three sector indices with the largest number of listed companies: the finance sector (15 companies), the distribution sector (7 companies) and the industry sector (7 companies).

❖ ***Description and justification of the choice of study variables*** Unlike previous studies, in this article we use:

- *Transaction volume*: according to Wen et al. (2014b), transaction volume reflects the commercial flow that underpins the supply and demand factors operating on the stock market. Therefore, considering transaction volume as an indicator of investor sentiment seems to be a reasonable starting point.
- *The price-earnings ratio (PER)* can be considered a good indicator for evaluating stock prices. Shiller and Campbell (2001) argue that the PER reliably predicts stock price movements in that it is most often used to judge the deviation of prices from their fundamental value.
- *Inflation rate (real interest rate):* several studies (Nelson, 1976; Schwartz & Whitcomb, 1977; Blanchard, 1993) have shown that stock market returns are negatively correlated with inflation. Others have most often cited interest rate trends as an excellent indicator for preventing financial crises (Baker and Wurgler, 2007).
- *The number of securities traded per day* reflects financial health but also changes in investor confidence in the stock market. It is one of the important variables, after the transaction volume and the number of new listed companies (new entrants to the stock market), in giving an idea of the direction of

the market (Beker and Wurgler, 2007).

- *The average rate of return* is the average of the rates of return on listed shares that have distributed a dividend.
- *The average market liquidity ratio* is the ratio of daily trading value to market capitalisation (trading value/market capitalisation). It gives us an indication of the financial health of the market.
- *The average trend ratio* is the average ratio of the volume of sell orders to the volume of buy orders. It is a measure of the stock market trend.
- *The average satisfaction ratio* is the ratio of the number of securities traded to the volume of buy orders.

4. Econometric Methodologies and Analysis Models

In this section of the research, we will describe the chosen research methodology. We will then outline the procedure for constructing indicators to measure investor sentiment and calendar anomalies.

4.1. Construction of the Investor Sentiment Index

To construct the investor sentiment indicator, we drew inspiration from the work of Huang et al. (2015), who used and improved upon the technique proposed by Baker and Wurgler (2007). For them, it is important first of all to disaggregate the volume of transactions, as this reflects both economic fundamentals and investor sentiment. To remove the structural effect, we regress the volume of transactions on a macroeconomic indicator (the interest rate), then use the regression residuals as the part representing investor sentiment, as follows:

$$Volume_t = f\left(taux\ d'\ int\ e\ ret\right) + TV_t \tag{1}$$

where $Volume_t$ represents the set of explanatory variables in the model, whose values are expressed on a daily basis, and TV_t can be considered as an indicator of investor sentiment. To assess the relationship between investor sentiment, stock returns and changes in stock market direction, we proceed as follows:

$$V_t = \begin{cases} 1\ Si\ TV_t > \dfrac{TV_{t-1} + TV_{t-2} + TV_{t-3} + TV_{t-4} + TV_{t-5}}{5} \\ 0\ SINON \end{cases}$$

TV represents the share of investor sentiment in trading volume. V_t is a dummy variable (dichotomous variable) that takes the value 1 whenever TV exceeds the previous week's average (average of the last 5 days), and 0 otherwise, as above.

Dummy variables associated with the days of the week (DMonday, DTuesday, DWednesday, DThursday and DFriday) corresponding to Monday, Tuesday, Wednesday, Thursday and Friday and the months of the year (DMonth, DFebruary, DMarch, DMarch, MMay, MJune, MJuly, MAugust, MSeptember, MOctober, MNovember, MDecember) corresponding to January, February, March, April, May, June, July, August, September, October, November and December will be used with V_t to validate our hypothesis concerning the effect of calendar anomalies on stock market returns and changes in market direction.

We define R_t as the return on date t as follows:

$$R_t = 100\left(\ln P_t - \ln P_{t-1}\right) \quad (2)$$

where P_t is the closing price of the index on date *t*.

Hong and Stein (2007) showed that there may be a positive relationship between trading volume and returns, as trading volume can reflect investor sentiment. The following models initially aim to prove the existence of calendar anomaly effects on the market. But they also aim to show that investor sentiment has a positive effect on stock market returns and the orientation of the BRVM market.

In fact, $TV_t = \varepsilon_t$ and comes from the initial equation $Volume_t = f\left(taux\ d'\ int\ e\ ret\right) + \varepsilon_t$, reformulated in the following form: $Volume_t = f\left(taux\ d'\ int\ e\ ret\right) + TV_t$, in our article. In short, TV_t is the series of residuals resulting from the regression of Equation (1).

V_t is a dummy variable that we have constructed. There are five (5) trading days on the BRVM (Monday, Tuesday, Wednesday, Thursday and Friday). We therefore start from the assumption that there is one day of the week among the five trading days on which transactions are abnormally high (high volume of purchase and sale transactions). This is generally due to certain calendar anomalies such as the effects of weekdays or weekends, etc. Thus, if we choose, for example, the **Monday** of the second week of our sample as the day with the highest trading volume, in this case.

Monday will be considered the day when investor sentiment will be highest. V_t takes the value 1 if the average of the residuals (TV_t) of the previous days ($TV_{\text{(Friday)}}$ + $TV_{\text{(Thursday)}}$ + $TV_{\text{(Wednesday)}}$ + $TV_{\text{(Tuesday)}}$ + $TV_{\text{(Monday)}}$ divided by 5) is less than $TV_{(t)}$ and the value 0 otherwise.

Dlundi Or MJanuary are also dummy variables constructed from the returns of the BRVM indices.

We assume that there is a day of the week or a month of the year that records an abnormally high level of returns on the BRVM indices. D is the initial of the day of the week and M is the initial of the month of the year. Thus, if DMonday = 1, this means that Monday's return is greater than that of the other days of the week in question, otherwise 0, according to the chosen BRVM index. The same applies to JJanuary.

4.2. Presentation of Model 1: The Linear Regression Model

An ordinary linear regression is used to show the presence of a positive effect of investor sentiment on stock market returns. Stock returns are regressed against investor confidence and dummy variables for the day of the week.

$$\begin{aligned} R_t = {} & \alpha_1 + \beta_1 V_t + \gamma_1 Dlundi + \gamma_2 Damrdi + \gamma_3 Dmercred + \gamma_4 Djeudi \\ & + Dvendre + v_t \end{aligned} \quad (3)$$

Here, to create our dummy variables, we assume that there is a day when returns are likely to be at their highest level compared to other days. On that day, we assign a value of 1 if it has the highest return, and the other days are assigned a value of zero (0) in a given week. For the following week, the next day takes the value 1 and the other days take zero (0). This continues until the last week of our data sample. We then regress the stock market return based on investor sentiment and dummy variables for the months of the year as follows:

$$\begin{aligned} R_t &= \alpha_2 + \beta_2 V_t + \lambda_1 Mjanvier + \lambda_2 Mfevrier + \lambda_3 Mmars + \lambda_4 Mavril + \lambda_5 Mmai \\ &+ \lambda_6 Mjuin + \lambda_7 Mjuillet + \lambda_8 Maout + \lambda_9 Mseptevbre + \lambda_{10} Moctobre \\ &+ \lambda_{11} Mnovembre + \lambda_{12} Mdecembre + \psi_t \end{aligned} \quad (4)$$

Here again, as with the days of the week, we assume that there is one month of the year in which stock market returns are at their highest level compared to other months. Thus, the same coding as for the dummy variables for the days of the week is applied to the months of the year.

We will now move on to the presentation of the second model, in our study.

4.3. Presentation of Model 2: The Logit Model

In this section, we will briefly present the context of the Logit model before justifying our choice of it. The Logit model is used to model the effect of a vector of random variables called "explanatory variables" on a binomial random variable or multinomial. It is used in many areas and sectors of the economy, including labour economics, demography, medicine and finance. There are two possible directions for the stock market: either upward (return greater than zero) or downward (return less than or equal to zero). Based on the work of Hirshleifer and Shumway (2003), a binomial Logit regression is used to prove that investor sentiment has a positive effect on the direction of the stock market. The authors use a model in which the probability of a positive return is positively correlated with the total sky coverage (SKC), which ranges from 0 (clear) to 8 (overcast), as follows:

$$\Pr\left(r_{it} > 0\right) = \frac{e^{r_i SKC_{it}}}{1 + e^{r_i SKC_{it}}}$$

Thus, assuming that a positive return means a rising market, then the possibility of a rising market can be defined as follows:

$$\Pr\left(R_t > 0 \middle| X_t\right) = \Pr\left(Y = 1 \middle| X_t\right) = p \quad (5)$$

While the probability of a bear market is:

$$\Pr\left(R_t \le 0 \middle| X_t\right) = \Pr\left(Y_t = 0 \middle| X_t\right) = 1 - p \quad (6)$$

where Y follows a Bernoulli distribution.

According to Greene (1997), a Logit model can be constructed by defining $\Pr\left(R_t > 0\right)$ as the probability of positive returns or a bull market as follows:

$$\Pr\left(R_t > 0\right) = \frac{e^{\beta V_t + \gamma_1 Dlundi + \gamma_2 Dmercredi + \gamma_3 Djeudi + \gamma_4 Dvendredi}}{1 + e^{\beta V_t + \gamma_1 Dlundi + \gamma_2 Dmercredi + \gamma_3 Djeudi + \gamma_4 Dvendredi}} \quad (7)$$

Knowing the probability of a bear market as follows:

$$\Pr\left(R_t \le 0\right) = \frac{1}{1+e^{\beta V_t+\gamma_1 Dlundi+\gamma_2 Dmercredi+\gamma_3 Djeudi+\gamma_4 Dvendredi}} \quad (8)$$

The ratio between the two probabilities (bullish and bearish market) gives us the odds ratio as follows:

$$Odds\left(\Pr\right) = \frac{\Pr\left(R_t > 0\right)}{\Pr\left(R_t \le 0\right)} = e^{\beta V_t+\gamma_1 Dlundi+\gamma_2 Dmercredi+\gamma_3 Djeudi+\gamma_4 Dvendredi} \quad (9)$$

Thus, in order to facilitate regression, economic theory argues that Equation (9) must be linearised.

To do this, we apply the natural logarithm (L) to this equation to obtain the following relationship:

$$L = \log\left[odds\left(\Pr\right)\right] = \frac{\Pr\left(R_t > 0\right)}{\Pr\left(R_t \le 0\right)} = \log\left(e^{\beta V_t+\gamma_1 Dlundi+\gamma_2 Dmercredi+\gamma_3 Djeudi+\gamma_4 Dvendredi}\right)$$

Finally, the logarithm of the odds ratio is given by the following Equation (10):

$$L = \log\left[Odds\left(\Pr\right)\right] = \beta V_t + \gamma_1 Dlundi + \gamma_2 Dmercredi + \gamma_3 Djeudi + \gamma_4 Dvendre \quad (10)$$

These two models (linear model and binomial logit model) attempt to predict: i) the existence of the effect of calendar anomalies and investor sentiment on stock market returns; and ii) a positive effect of investor sentiment on market direction.

5. Presentation and Discussion of Result

This section will present the various results of the study, starting with descriptive statistics, the ARCH effect, unit root tests, and ending with model estimates.

5.1. Descriptive Statistics of the Returns of the Various BRVM Indices

Table 1 and Table 2 present descriptive statistics of the returns of the two sector indices with the largest number of companies. These statistics are sorted according to the dummy variables of investor sentiment and day of the week. Obviously, when investor sentiment is above the previous week's average ($V_t = 1$), the mean value and standard deviation are significantly higher for each index. In addition, the mean return is often negative when investor sentiment is below the weekly average. It can also be noted that the effect of the day of the week is not the same for all returns. With the results in Table 1 and Table 2, it is easy to verify that the return and variance are much higher when $V = 1$. This result implies that the more optimistic investors are, the more they trade on the stock market. Their confidence is thus reflected in the increase in the returns on BRVM securities. The most significant observation is that two out of five indices show negative average returns when $V = 0$. This trend shows that when investors are pessimistic, returns are likely to be very low (even negative) and vice versa.

Table 3 shows the statistics for stock market returns when $V = 0$ and $V = 1$ for

BRDI[6] , BRVM 10 and BRVM Composite. This table presents a set of descriptive statistics for the BRVM return series. The standard deviations reflect the volatility of stock market returns through their tendency to deviate significantly from their means. In the standard deviations range from 0.321 to 1.675 for the BRVMC, with a variation in the mean from −0.029 for the BRVM 10 to 0.034 for the BRDI. For normally distributed series, the skewness coefficient and the kurtosis coefficient are equal to 0 and 3, respectively.

Table 1. Descriptive statistics of BRVM finance yield (BRFI[7]).

BRFI	N	Average	Maximum	Minimum	Standard deviation
$V = 0$	1393	**−0.017**	21.909	−20.454	0.098
$V = 1$	800	0.075	17.675	−18.567	2.032
MONDAY	429	0.025	10.561	−9.654	0.321
TUESDAY	452	−0.057	16.543	−13.564	1.021
WEDNESDAY	439	0.012	17.788	−14.009	0.042
THURSDAY	450	−0.029	13.342	−10.675	1.321
FRIDAY	423	0.057	14.433	−11.091	0.823

Note: $V = 1$ indicates that investor sentiment is higher than the previous week's average, and $V = 0$ indicates the opposite. Maximum and Minimum indicate the highest and lowest stock market returns.

This indicates that the distribution of the series is asymmetrical and sometimes skewed to the left (for negative skewness) or to the right (positive skewness) depending on the different indices. In addition, the return series is leptokurtic, as the kurtosis coefficients are well above 3, ranging from 30.564 for the BRVM composite to 89.547 for the BRVM 10. As for the Jarque-Bera statistic and its associated probability, they indicate that the null hypothesis of normal distribution of returns is rejected at the 1% threshold.

Table 2. Descriptive Statistics of the BRVM Industry Return (BRIN[8]).

BRIN	N	Mean	Maximum	Min	Standard deviation
$V = 0$	874	−0.043	23.098	−19.72	0.198
$V = 1$	1300	0.065	17.432	−10.71	0.201
MONDAY	443	0.034	14.432	−8.321	1.032
TUESDAY	465	0.003	12,092	−19.23	0.218
WEDNESDAY	422	0.021	21,500	−6.129	0.023
THURSDAY	426	0.042	12.221	−20.02	0.245
FRIDAY	418	0.048	16.201	−9.328	1.091

Note: Monday, Tuesday, Wednesday, Thursday and Friday are indicators of the effect of calendar anomalies (day of the week effect).

[6]BRDI here represents the BRVM sector index, which tracks companies in the distribution sector.
[7]BRFI represents the BRVM sector index that tracks companies in the finance sector.
[8]BRIN represents the BRVM sector index that tracks companies in the industrial sector.

Our results (Table 3) reveal skewness coefficients ranging from −0.769 for BRDI to 0.256 for the composite BRVM, all of which are different from 0.

According to research by Alberg et al. (2008) and Huang et al. (2015), this asymmetry may be a sign of non-linearity in the process of stock market returns.

Table 3. Descriptive statistics for the returns of the various indices.

Indices	V_t	Average	Max	Min	Standard deviation	Skewness	Kurtosis	Jarque-Bera stat.
Brvm10	0	−0.017	21.909	−20.454	1.098	−0.043	89.547	48564.45***(0.00)
	1	0.005	17.675	−18.567	0.333	−0.432	77.425	45765.53***(0.00)
BRVM C	0	0.021	10.561	−9.654	0.321	0.248	33.564	35675.52***(0.00)
	1	0.024	14.324	−7.880	1.675	0.256	30.564	37895.55***(0.00)
BRDI	0	−0.029	13.342	−10.675	1.321	−0.769	45.342	47435.43***(0.00)
	1	0.034	12.453	−12.651	1.324	−0.426	37.536	56786.65***(0.00)

Notes: (***) indicates significance at the 1% level, (**) indicates significance at the 5% level, (*) indicates significance at the 10% level.

This possible non-linearity may indicate the presence of an ARCH (autoregressive conditional heteroscedasticity) effect, which is frequently encountered in financial series. Table 4 below presents the results of the ARCH effect tests according to the approach of Mcleod and Li (1983) and that of Engle's (1982) Lagrange multiplier.

5.2. The Results of the ARCH Effect Test

Table 4 presents the results of the ARCH (Autoregressive Conditional Heteroscedasticity) effect, which could be the cause of non-linearity in the process of profitability evolution, using two different methods: The method proposed by Engle (1982), which consists of estimating ε_t by $\hat{\varepsilon}_t$.

That is, performing regression of the model $\hat{\varepsilon}_t = \partial_0 + \partial_1 \hat{\varepsilon}_{t-1}^2 + \cdots + \partial_p \hat{\varepsilon}_{t-p}^2 + v_t$ and calculating TR^2 with T, the sample size, and $T \times R \sim \boldsymbol{X}^2$. Then that of Mcloed and Li (1983), which is a test similar to the Ljung-Box test, except that here it is the squared residuals that are evaluated.

That is $Q^2(m) = T(T+2)\sum_{j=1}^{m}\frac{\hat{e}_j}{T-j}$. The Mcleod and Li test gives statistical values of 244.63 for the BRVM 10 with an optimal lag of 8 days and 212.77 for the composite BRVM with a lag of 5 days. The p-values associated with this statistic are 2.2e−16, which is less than (5%). This result allows us to reject the null hypothesis of no heteroscedasticity.

Next, Engle's LM test gives F-statistics of 21.18 for the BRVM 10 and 15.75 for the composite index, with p-values below 5% (Table 4). The results of both tests confirm the existence of heteroscedasticity (ARCH effect) in the evolution of the BRVM return series. This effect would therefore be the cause of the non-linearity observed in the evolution of the indices' profitability. Before the econometric estimates, we performed several stationarity tests on the BRVM returns. Three unit root tests were used, including the augmented Dickey-Fuller (ADF) test, the

Philips and Perron test, and the Elliot-Rothenberg and Stock test. The t-statistics obtained are compared to the different critical values in parentheses in Table 5 below. Analysis of this table shows that the statistical values of all three tests are lower than the various critical values. Hence the rejection of the null hypothesis of non-stationarity (presence of a unit root). The tests carried out therefore all confirm the stationarity of the returns of our various indices, in particular the BRVM10, the BRVM distribution, the BRVM finance and the BRVM composite.

Table 4. Macleod's ARCH test and Engle's Lagrange multiplier test.

Returns \ ARCH effect test	Ljung-Box method according to Mcleod	Lagrange multiplier method according to Engle
BRVM 10	Q^2(m) = 244.63; m = 1 p-value = 2.2 e−16	F-stat = 21.18; m = 1 p-value = 2.2 e−16
BRVM Composite	Q^2 (m) = 212.77; m = 5 p-value = 2.2 e−16	F-stat = 15.75; m = 5 P-value = 2.2 e−16
BRFI	Q^2 (m) = 209.49; m = 2 p-value = 2.2 e−16	F-stat = 18.34; m = 2 p-value = 2.2 e−16
BRIN	Q^2 (m) = 222.19; m = 5 p-value = 2.2 e−16	F-stat = 28.67; m = 5 p-value = 2.2 e−16

Note: null hypothesis H0: if $\alpha_1 = \alpha_2 = \cdots = 0$, absence of heteroscedasticity. Here (m) represents the optimal lag in terms of day of the week for the two indices. F-stat is the associated Fisher statistic.

Table 5. Unit root or data stationarity tests.

BRVM10	Stat. ERS	ADF Stat.	Stat. pp
	−22.616** (−1.94)	−26.126** (−2.56)	−28.101** (−2.56)
BRVMC	−8.321** (−1.94)	−13.524** (−2.56)	−27.135** (−2.56)
BRDI	−10.564** (−1.94)	−16.075** (−2.56)	−22.564** (−2.56)
BRFI	−27.453** (−1.94)	−20.312** (−2.56)	−21.743** (−2.56)

Notes: Stat. ADF is the value of the Augmented Dickey-Fuller statistic to be compared with the critical value of −2.56 at the 5% threshold. Asterisks indicate significant values. Stat. Pp is the value of the Philips and Perron statistic. Stat. ERS is the value of the Elliott-Rothenberg-Stock statistic to be compared with the critical value of −1.94 at the 5% threshold. (**) indicates significance at the 5% level, (*) indicates significance at the 10% level.

5.3. Impact of Investor Sentiment on Stock Market Returns

An ordinary linear regression is used to analyse the effect of investor sentiment on stock market returns. Index returns are regressed against investor sentiment and dummy variables for the day of the week. According to the cross-tabulation analysis, Tuesday has the highest number of times where $V = 1$. It is therefore chosen as the reference day, and Monday, Wednesday, Thursday and Friday are selected as control days for the week. The same experiment will be repeated over the eleven months of the year, using March as the reference month, as follows:

$$R_t = \alpha_1 + \beta_1 V_t + \gamma_1 Dlundi + \gamma_2 Dmerc + \gamma_3 Djeu + \gamma_4 Dvendredi + v_t \tag{11}$$

Anomalies (the month effect) are determined using the following equation:

$$R_t = \alpha_2 + \beta_2 V_t + \lambda_1 Mjanvier + \lambda_2 Mfevrier + \lambda_3 Mavril + \lambda_4 Mmai + \lambda_5 Mjuin + \lambda_6 Mjuillet + \lambda_7 Maout + \lambda_8 Mseptevbre + \lambda_9 Moctobre + \lambda_{10} Mnovembre + \lambda_{11} Mdecembre + \psi_t \quad (12)$$

The result of the ordinary linear regression presented in Table 6 suggests that there is a positive relationship between stock market returns and investor sentiment. The result is consistent with what was expected in that all parameters relating to investor sentiment are positive and significant at 5%. This indicates that if investor sentiment on a given day is positive, it has a positive effect on stock market returns. However, it is difficult to conclude whether the day of the week effect exists for all returns. It is true that the Monday effect appears for some returns (BRVM 10 and BRDI), while for others the effect is not significant.

5.4. Impact of Investor Sentiment on Stock Market Trends

Numerous studies have analysed the relationship between trading volume and stock market returns (Hong & Stein, 2007; Shu & Chang, 2015; Gong et al., 2016; Ren et al., 2018, etc.). According to some conclusions, positive stock market returns indicate a rising market, while negative stock market returns indicate a falling market. Given this hypothesis, a Logit regression was used. The results obtained were then compared with those obtained by the linear regression above. Specifically, the major contribution of this study was to prove that positive investor sentiment has a positive effect on index returns and to test the relationship between market direction and investor sentiment.

Table 6 and Table 7 below show the results of the linear and logistic model estimates based on the investor confidence index and the days of the week.

Table 6. Results of parameter estimation by linear model regression.

INDICES	Investor Sentiment	Monday	Tuesday	Wednesday	Thursday
BRVM10	0.2455** (0.023)	−0.675** (0.046)	0.099 (0.567)	−0.009 (0.900)	0.878 (0.068)
BRVM C	0.172** (0.034)	0.986 (0.984)	−0.098 (0.897)	0.767 (0.675)	−0.056 (0.677)
BRFI	0.346 (0.003)	−0.564 (0.564)	−0.089 (0.597)	0.897 (0.986)	−0.897 (0.897)
BRIN	0.786 (0.013)	−0.676 (0.675)	−0.032 (0.798)	−0.118 (0.325)	0.786** (0.004)
BRDI	−0.628** (0.045)	−0.675** (0.038)	−0.653 (0.675)	−0.457* (0.075)	−0.675 (0.189)

Note: here (**) indicates significance at 5% and (*) indicates significance at 10%.

In this section, we assume that there are two possibilities in the market: making a profit, corresponding to a positive return, which means a rising market; or not making a profit, corresponding to a zero or negative return, which means a falling market. The results of the logistic regression model (**Table 7**) indicate that all investor sentiment coefficients are positive and statistically significant at 5%. This result implies that a bullish (bearish) market corresponds to optimistic (pessimistic) sentiment.

These results are consistent with the conclusions of Gervais and Odean (2001), who argue that extremely high trading volumes are due to overconfidence among investors. Indeed, capital gains (profits) on initial investments increase investors' confidence in their ability to manage their portfolios and encourage them to be more active by taking more risks in the market. At the aggregate level, this translates into an increase in trading volumes after prices rise. This situation then inevitably leads to the development of overconfidence, which in turn leads to increased risktaking.

Table 7. Results of parameter estimation using the Logit model.

INDICES	Investor sentiment	Monday	Tuesday	Wednesday	Thursday
BRVM10	0.542** (0.032)	0.842*** (0.001)	0.238 (0.432)	0.126 (0.154)	0.034 (0.543)
BRVM C	0.437 (0.012)	0.743 (0.453)	0.432 (0.321)	0.023 (0.051)	0.342 (0.123)
BRFI	0.765** (0.027)	0.321 (0.004)	0.643 (0.123)	0.465 (0.231)	0.093 (0.021)
BRIN	0.831** (0.035)	0.032 (0.432)	0.432 (0.439)	0.432 (0.151)	0.342 (0.543)
BRDI	0.034 (0.003)	0.003 (0.543)	0.723 (0.743)	−0.083*** (0.003)	0.324 (0.263)

Note: (***) indicates significance at 1%, (**) indicates significance at 5%.

Our results are consistent with the conclusions of several studies, notably those by De Long et al (1990); Baker and Wurgler (2006, 2007) and Baker et al. (2012); Huang et al., (2014 and 2015), etc.

Most of these studies have shown that investor sentiment plays an important role in stock price movements. Some, such as Baker and Wurgler (2006, 2007) and Baker et al. (2012), believe that taking investor sentiment into account in calculations is a sure way to improve the quality of stock market forecasts. They argue that, despite the difficulty of measuring investor sentiment, it appears to be the factor that most influences stock price movements. Similar to the results of linear regression, positive investor sentiment has a positive (negative) effect on the odds ratio at a significance level of 1%, which can be considered a positive (negative) effect on the direction of the stock market. The effect of the day of the week and the month of the year varies depending on the performance of each index.

Indeed, the regression of the Logit model using the McFadden method indicated a pseudo-R^2 e of 0.25, which more or less reflects a clear improvement in likelihood compared to the null model (without explanatory variables). This also reflects a satisfactory overall fit.

We also plotted the ROC curve based on sensitivity and 1-specificity (false positive rate). We also obtained an AUC (Area Under the ROC Curve) of 0.82, which suggests a high discriminatory capacity: the model correctly distinguishes approximately 82% of observations between the predicted modalities.

Taken together, these results show that the model has both a suitable fit and robust predictive power, making it a relevant tool for analysing our data set.

The results obtained in this study are consistent with those of several authors regarding the effect of investor sentiment. However, they contradict the results of most authors regarding the effect of calendar anomalies on stock market returns. Overall, we can include the results related to investor sentiment in the conclusions of the overconfidence theory developed by DHS [9](Daniel et al., 1998). This model stipulates that investors place too much weight on their own information and not enough on the public (market) information they receive. Investors' overreaction to their private information leads to negative autocorrelation of long-term returns (reversal).

Self-attribution bias prolongs this overreaction and causes positive autocorrelation of short-term returns (momentum). Indeed, the results indicate that BRVM investors are divided between the two emotional situations described by Daniel et al., (1998). Their behaviour initially suggests that they act without measuring the extent of the risk involved. Secondly, these results show that investors do not take full advantage of all the profit opportunities offered by the new dynamics of the BRVM. There are a multitude of studies that have analysed the effect of calendar anomalies on stock market returns in various markets. Most research on anomalies attests to the existence of a statistically significant link with stock market returns. This is the case with Hirshleifer and Shumway (2003), who, in order to relate the probability of a positive stock market return to cloudiness, opted for a Logit model in their examination of more than 26 international stock markets from 1982 to 1997. They concluded that stock market returns in the various markets in their sample were strongly correlated with sunshine. Subsequently, Loughran and Schultz, echoing the conclusions of Hirshleifer and Shumway (2003), stated that this finding clearly suggested that weather conditions may be linked to investor sentiment. This, in turn, influences stock market returns and, by ext, the direction of the market.

5.5. Results of the Effect of Investor Sentiment on Stock Market Returns

The results indicate that investor sentiment is positive and significant at 5% for the five BRVM indices following all trading days of the week. This result implies that positive investor sentiment (high level of confidence or optimism) leads to an increase in the profitability of the BRVM. This conclusion is consistent with those obtained by most empirical studies on this phenomenon. The positive effect of investor sentiment on stock market returns, as well as the importance of taking this indicator into account in analyses, has been proven by numerous studies (Naik & Padhi, 2016; Huang et al., 2014, 2015; Baker & Wurgler, 2006, 2007; De Long et al., 1990). According to these studies, investor sentiment has a consider-

[9]K. Daniel, D. Hirshleifer and A. Subrahmanyam (DHS, 1998) propose a model based on overconfidence and selfattribution biases to explain momentum and reversal effects.

able influence on the evolution of stock market returns.

They find no significant relationship between the investor sentiment indicator and the future performance of the Dow Jones and S&P 500. Using a synthetic measure of sentiment, Brown and Cliff (2004) find that it is stock returns that influence investor sentiment and not the other way around.

6. Conclusion

The conclusions of this thesis are in line with existing literature, with a certain original touch. With regard to the effect of the days of the week, our results differ from those initially expected. Our basic hypothesis was to prove that there are calendar anomalies (day effects and month effects). We then sought to show that these anomalies had a statistically significant effect on the performance of BRVM indices. However, the results indicate that there is no consensus on the effect of calendar anomalies, particularly those related to the days of the week, on BRVM returns. This is because anomalies related to the days of the week vary depending on the different indices.

We also found that there was a positive and significant effect of the month (January effect) on the stock market. We justified this result through the literature as the result of strategies developed by investors and various market players to either avoid high taxation or as an opportunity to take advantage of year-end bonuses to acquire more assets in order to expand and diversify their stock portfolios. The absence of a compromise on the day-of-the-week effect (Monday effect) could be explained by the fact that the BRVM is still a little-known market to the majority of the population in the WAEMU area. Nevertheless, our hypothesis regarding the positive effect of investor sentiment on stock market returns has been verified.

The Logit/Probit model is particularly appropriate for defining the relationship between investor sentiment and stock price movements, as the direction of stock market movements is binary in nature, i.e., either upward or downward. In recent years, a growing number of studies have also used Logit/Probit models to analyse the relationship between stock market returns and fundamental variables (Frankel & Rose, 1996; Demirgüç-Kunt & Detragiache, 2000; Bussiere & Fratzscher, 2006; etc.).

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

References

Abu-Mostafa, Y. S., & Atiya, A. F. (1996). Introduction to Financial Forecasting. *Applied Intelligence, 6,* 205-213. https://doi.org/10.1007/bf00126626

Ahmad Al-smadi, A. A., Almsafir, M. K., & Binti Husni, N. H. H. (2017). Trends and Calendar Effects in Malaysia's Stock Market. *Accounting and Finance Research, 6,* 18. https://doi.org/10.5430/afr.v6n1p18

Alberg, D., Shalit, H., & Yosef, R. (2008). Estimating Stock Market Volatility Using Asymmetric GARCH Models. *Applied Financial Economics, 18,* 1201-1208. https://doi.org/10.1080/09603100701604225

Aleknevičienė, V., Klasauskaitė, V., & Aleknevičiūtė, E. (2021). Behavior of Calendar Anomalies and the Adaptive Market Hypothesis: Evidence from the Baltic Stock Markets. *Journal of Baltic Studies, 53,* 187-210. https://doi.org/10.1080/01629778.2021.1990094

Alexakis, P., & Xanthakis, M. (1995). Day of the Week Effect on the Greek Stock Market. *Applied Financial Economics, 5,* 43-50. https://doi.org/10.1080/758527670

Arévalo, R., García, J., Guijarro, F., & Peris, A. (2017). A Dynamic Trading Rule Based on Filtered Flag Pattern Recognition for Stock Market Price Forecasting. *Expert Systems with Applications, 81,* 177-192. https://doi.org/10.1016/j.eswa.2017.03.028

Baker, M., & Wurgler, J. (2006). Investor Sentiment and the Cross-section of Stock Returns. *The Journal of Finance, 61,* 1645-1680. https://doi.org/10.1111/j.1540-6261.2006.00885.x

Baker, M., & Wurgler, J. (2007). Investor Sentiment in the Stock Market. *Journal of Economic Perspectives, 21,* 129-151. https://doi.org/10.1257/jep.21.2.129

Baker, M., Wurgler, J., & Yuan, Y. (2012). Global, Local, and Contagious Investor Sentiment. *Journal of Financial Economics, 104,* 272-287. https://doi.org/10.1016/j.jfineco.2011.11.002

Barberis, N., & Thaler, R. (2003). Chapter 18. A Survey of Behavioral Finance. In *Handbook of the Economics of Finance* (pp. 1053-1128). Elsevier. https://doi.org/10.1016/s1574-0102(03)01027-6

Barney, J. B. (2005). Should Strategic Management Research Engage Public Policy Debates? *Academy of Management Journal, 48,* 945-948. https://doi.org/10.5465/amj.2005.19573092

Bernanke, B. S., Boivin, J., & Eliasz, P. (2005). Measuring the Effects of Monetary Policy: A Factor-Augmented Vector Autoregressive (FAVAR) Approach. *Quarterly Journal of Economics, 120,* 387-422. https://doi.org/10.1162/qjec.2005.120.1.387

Bernstein, P. L. (2007). *Capital Ideas Evolving*. John Wiley & Sons.

Bhardwaj, R. K., & Brooks, L. D. (1992). The January Anomaly: Effects of Low Share Price, Transaction Costs, and Bid-Ask Bias. *The Journal of Finance, 47,* 553-575. https://doi.org/10.1111/j.1540-6261.1992.tb04401.x

Blanchard, O. (1993). Consumption and the Recession of 1990-1991. *The American Economic Review, 83,* 270-274.

Brown, G. W. (1999). Volatility, Sentiment, and Noise Traders. *Financial Analysts Journal, 55,* 82-90. https://doi.org/10.2469/faj.v55.n2.2263

Brown, G. W., & Cliff, M. T. (2004). Investor Sentiment and the Near-Term Stock Market. *Journal of Empirical Finance, 11,* 1-27. https://doi.org/10.1016/j.jempfin.2002.12.001

Bussiere, M., & Fratzscher, M. (2006). Towards a New Early Warning System of Financial Crises. *Journal of International Money and Finance, 25,* 953-973. https://doi.org/10.1016/j.jimonfin.2006.07.007

Cross, F. (1973). The Behavior of Stock Prices on Fridays and Mondays. *Financial Analysts Journal, 29,* 67-69. https://doi.org/10.2469/faj.v29.n6.67

Da, Z., Engelberg, J., & Gao, P. (2015). The Sum of All FEARS Investor Sentiment and Asset Prices. *Review of Financial Studies, 28,* 1-32. https://doi.org/10.1093/rfs/hhu072

Damasio, A. R. (1994). Descartes' Error and the Future of Human Life. *Scientific American, 271,* 144-144. https://doi.org/10.1038/scientificamerican1094-144

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor Psychology and Security

Market Under- and Overreactions. *The Journal of Finance, 53,* 1839-1885. https://doi.org/10.1111/0022-1082.00077

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise Trader Risk in Financial Markets. *Journal of Political Economy, 98,* 703-738. https://doi.org/10.1086/261703

Demirguc-Kunt, A., & Detragiache, E. (2000). Monitoring Banking Sector Fragility: A Multivariate Logit Approach. *The World Bank Economic Review, 14,* 287-307. https://doi.org/10.1093/wber/14.2.287

Dicle, M. F., & Levendis, J. D. (2014). The Day-of-the-Week Effect Revisited: International Evidence. *Journal of Economics and Finance, 38,* 407-437. https://doi.org/10.1007/s12197-011-9223-6

Edmans, A., García, D., & Norli, Ø. (2007). Sports Sentiment and Stock Returns. *The Journal of Finance, 62,* 1967-1998. https://doi.org/10.1111/j.1540-6261.2007.01262.x

Eleswarapu, V. R., & Reinganum, M. R. (1993). The Seasonal Behavior of the Liquidity Premium in Asset Pricing. *Journal of Financial Economics, 34,* 373-386. https://doi.org/10.1016/0304-405x(93)90032-7

Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica, 50,* 987-1007. https://doi.org/10.2307/1912773

Fama, E. F. (1965). The Behavior of Stock-Market Prices. *The Journal of Business, 38,* 34-105. https://doi.org/10.1086/294743

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance, 25,* 383-417. https://doi.org/10.2307/2325486

Fama, E. F. (1995). Random Walks in Stock Market Prices. *Financial Analysts Journal, 51,* 75-80. https://doi.org/10.2469/faj.v51.n1.1861

Fisher, K. L., & Statman, M. (2000). Investor Sentiment and Stock Returns. *Financial Analysts Journal, 56,* 16-23. https://doi.org/10.2469/faj.v56.n2.2340

Frankel, J. A., & Rose, A. K. (1996). Currency Crashes in Emerging Markets: An Empirical Treatment. *Journal of International Economics, 41,* 351-366. https://doi.org/10.1016/s0022-1996(96)01441-9

French, K. (1980). Stock Returns and the Weekend Effect. *Journal of Financial Economics, 8,* 55-69. https://doi.org/10.1016/0304-405X(80)90021-5

Fung, K. W. T., Demir, E., Lau, C. K. M., & Chan, K. H. (2015). Reexamining Sports-Sentiment Hypothesis: Microeconomic Evidences from Borsa Istanbul. *Journal of International Financial Markets, Institutions and Money, 34,* 337-355. https://doi.org/10.1016/j.intfin.2014.11.015

Gebka, B. (2013). The Non-Linear and Linear Impact of Investor Sentiment on Stock Returns: An Empirical Analysis of the US Market. In *Recent Advances in Estimating Nonlinear Models: With Applications in Economics and Finance* (pp. 281-299). Springer. https://doi.org/10.1007/978-1-4614-8060-0_13

Gervais, S., & Odean, T. (2001). Learning to Be Overconfident. *Review of Financial Studies, 14,* 1-27. https://doi.org/10.1093/rfs/14.1.1

Gibbons, M. R., & Hess, P. (1981). Day of the Week Effects and Asset Returns. *The Journal of Business, 54,* 579-596. https://doi.org/10.1086/296147

Gong, X., Wen, F., Xia, X.H., Huang, J., and Pan, B. (2016). Investigating the Risk-Return Tradeoff for Crude Oil Futures Using High-Frequency Data. *Applied Energy, 15,* Article ID: 3567112.

Gouider, J. J., Kaddour, A., & Hmaid, A. (2015). Stock Market Anomalies: Case of Calendar Effects on the Tunisian Stock Market. *Global Journal of Management and Business Research: B Economics and Commerce, 15,* 1-12.

Gultekin, M. N., & Gultekin, N. B. (1983). Stock Market Seasonality: International Evidence. *Journal of Financial Economics, 12,* 469-481. https://doi.org/10.1016/0304-405x(83)90044-2

Hirshleifer, D., & Shumway, T. (2003). Good Day Sunshine: Stock Returns and the Weather. *The Journal of Finance, 58,* 1009-1032. https://doi.org/10.1111/1540-6261.00556

Hong, H., & Stein, J. C. (2007). Disagreement and the Stock Market. *Journal of Economic Perspectives, 21,* 109-128. https://doi.org/10.1257/jep.21.2.109

Hu, W., Huang, Y., Wei, L., Zhang, F., & Li, H. (2015). Deep Convolutional Neural Networks for Hyperspectral Image Classification. *Journal of Sensors, 2015,* Article ID: 258619. https://doi.org/10.1155/2015/258619

Huang, C., Yang, X., Yang, X., & Sheng, H. (2014). An Empirical Study of the Effect of Investor Sentiment on Returns of Different Industries. *Mathematical Problems in Engineering, 2014,* Article ID: 545723. https://doi.org/10.1155/2014/545723

Huang, D., Jiang, F., Tu, J., & Zhou, G. (2015). Investor Sentiment Aligned: A Powerful Predictor of Stock Returns. *The Review of Financial Studies, 28,* 791-837. https://doi.org/10.1093/rfs/hhu080

Jaffe, J., & Westerfield, R. (1985). The Week-End Effect in Common Stock Returns: The International Evidence. *The Journal of Finance, 40,* 433-454. https://doi.org/10.1111/j.1540-6261.1985.tb04966.x

Jebran, K., & Chen, S. (2017). Examining Anomalies in Islamic Equity Market of Pakistan. *Journal of Sustainable Finance & Investment, 7,* 275-289. https://doi.org/10.1080/20430795.2017.1289455

Kahneman, D., & Smith, V. (2002). Foundations of Behavioral and Experimental Economics. *Nobel Prize in Economics Documents*, 1, 1-25

Keim, D. B. (1983). Size-Related Anomalies and Stock Return Seasonality: Further Empirical Evidence. *Journal of Financial Economics, 12,* 13-32. https://doi.org/10.1016/0304-405x(83)90025-9

Khan, K., Nasir, M. A., & Rossi, M. (2017). The Calendar Anomalies on Performance and Volatility of Stock Market: The Effects of Ramadan on Karachi Stock Exchange. *Global Business and Economics Review, 19,* 54-69. https://doi.org/10.1504/gber.2017.080775

Kling, G., & Gao, L. (2008). Chinese Institutional Investors' Sentiment. *Journal of International Financial Markets, Institutions and Money, 18,* 374-387. https://doi.org/10.1016/j.intfin.2007.04.002

Krivelyova, A., & Robotti, C. (2003). *Playing the Field: Geomagnetic Storms and International Stock Markets (No. 2003-5a).* Working Paper.

Lee, W. Y., Jiang, C. X., & Indro, D. C. (2002). Stock Market Volatility, Excess Returns, and the Role of Investor Sentiment. *Journal of Banking & Finance, 26,* 2277-2299. https://doi.org/10.1016/s0378-4266(01)00202-3

Lemmon, M., & Portniaguina, E. (2006). Consumer Confidence and Asset Prices: Some Empirical Evidence. *Review of Financial Studies, 19,* 1499-1529. https://doi.org/10.1093/rfs/hhj038

Liu, J., Tao, M., Ma, C., & Wen, F. (2014). Utility Indifference Pricing of Convertible Bonds. *International Journal of Information Technology & Decision Making, 13,* 429-444. https://doi.org/10.1142/s0219622014500527

Lucas, R. E. (1978). Asset Prices in an Exchange Economy. *Econometrica, 46,* 1429-1445. https://doi.org/10.2307/1913837

Lutz, C. (2016). The Asymmetric Effects of Investor Sentiment. *Macroeconomic Dynamics, 20,* 1477-1503. https://doi.org/10.1017/s1365100514000996

McLeod, A. I., & Li, W. K. (1983). Diagnostic Checking Arma Time Series Models Using Squared-Residual Autocorrelations. *Journal of Time Series Analysis, 4,* 269-273. https://doi.org/10.1111/j.1467-9892.1983.tb00373.x

Michael, J. R., Schucany, W. R., & Haas, R. W. (1976). Generating Random Variates Using Transformations with Multiple Roots. *The American Statistician, 30,* 88-90. https://doi.org/10.1080/00031305.1976.10479147

Naik, P. K., & Padhi, P. (2016). Investor Sentiment, Stock Market Returns and Volatility: Evidence from National Stock Exchange of India. *International Journal of Management Practice, 9,* 213-237. https://doi.org/10.1504/ijmp.2016.077816

Nelson, C. R. (1976). Inflation and Rates of Return on Common Stocks. *The Journal of Finance, 31,* 471-483. https://doi.org/10.1111/j.1540-6261.1976.tb01900.x

Nguyen, T., Locke, S., & Reddy, K. (2015). Ownership Concentration and Corporate Performance from a Dynamic Perspective: Does National Governance Quality Matter? *International Review of Financial Analysis, 41,* 148-161. https://doi.org/10.1016/j.irfa.2015.06.005

Nivoix, S., & Boulerne, S. (2020). The Monday Effect on Central and Eastern European Markets: A Factor to Be Included in an International Investment Strategy? *Management International, 24,* 138-152. https://doi.org/10.7202/1072647ar

Odean, T. (1998). Volume, Volatility, Price, and Profit When All Traders Are above Average. *The Journal of Finance, 53,* 1887-1934. https://doi.org/10.1111/0022-1082.00078

Olson, D., Mossman, C., & Chou, N. (2015). The Evolution of the Weekend Effect in US Markets. *The Quarterly Review of Economics and Finance, 58,* 56-63. https://doi.org/10.1016/j.qref.2015.01.005

Park, C., & Irwin, S. H. (2007). What Do We Know about the Profitability of Technical Analysis? *Journal of Economic Surveys, 21,* 786-826. https://doi.org/10.1111/j.1467-6419.2007.00519.x

Pena, J. I. (1995). Daily Seasonalities and Stock Market Reforms in Spain. *Applied Financial Economics, 5,* 419-423. https://doi.org/10.1080/758538601

PH, H., & Rishad, A. (2020). An Empirical Examination of Investor Sentiment and Stock Market Volatility: Evidence from India. *Financial Innovation, 6,* 1-15. https://doi.org/10.1186/s40854-020-00198-x

Rapach, D., & Zhou, G. (2013). Forecasting Stock Returns. In *Handbook of Economic Forecasting* (pp. 328-383). Elsevier. https://doi.org/10.1016/b978-0-444-53683-9.00006-2

Ren, R., Wu, D. D., & Liu, T. (2018). Forecasting Stock Market Movement Direction Using Sentiment Analysis and Support Vector Machine. *IEEE Systems Journal, 13,* 760-770. https://doi.org/10.1109/jsyst.2018.2794462

Rozeff, M. S., & Kinney, W. R. (1976). Capital Market Seasonality: The Case of Stock Returns. *Journal of Financial Economics, 3,* 379-402. https://doi.org/10.1016/0304-405x(76)90028-3

Sayim, M., Morris, P. D., & Rahman, H. (2013). The Effect of US Individual Investor Sentiment on Industry-Specific Stock Returns and Volatility. *Review of Behavioural Finance, 5,* 58-76. https://doi.org/10.1108/rbf-01-2013-0006

Schwartz, R. A., & Whitcomb, D. K. (1977). Evidence on the Presence and Causes of Serial

Correlation in Market Model Residuals. *The Journal of Financial and Quantitative Analysis, 12,* 291-313. https://doi.org/10.2307/2330436

Sewraj, D., Gebka, B., & Anderson, R. D. J. (2019). Day-of-the-Week Effects in Financial Contagion. *Finance Research Letters, 28,* 221-226. https://doi.org/10.1016/j.frl.2018.05.002

Shefrin, H. (2005). *A Behavioral Approach to Asset Pricing*. Academic Press/Elsevier.

Shiller, R. J. (2000). Measuring Bubble Expectations and Investor Confidence. *Journal of Psychology and Financial Markets, 1,* 49-60. https://doi.org/10.1207/s15327760jpfm0101_05

Shiller, R. J. (2003). From Efficient Markets Theory to Behavioral Finance. *Journal of Economic Perspectives, 17,* 83-104. https://doi.org/10.1257/089533003321164967

Shiller, R. J., & Campbell, J. Y. (2001). *Valuation Ratios and the Long-Run Stock Market Outlook: An Update*. National Bureau of Economic Research.

Shu, H. C., & Chang, J. H. (2015). Investor Sentiment and Financial Market Volatility. *Journal of Behavioral Finance, 16,* 206-219. https://doi.org/10.1080/15427560.2015.1064930

Stambaugh, R. F., Yu, J., & Yuan, Y. (2012). The Short of It: Investor Sentiment and Anomalies. *Journal of Financial Economics, 104,* 288-302. https://doi.org/10.1016/j.jfineco.2011.12.001

Thaler, R. H. (1999). Mental Accounting Matters. *Journal of Behavioral Decision Making, 12,* 183-206. https://doi.org/10.1002/(sici)1099-0771(199909)12:3<183::aid-bdm318>3.0.co;2-f

Thaler, R. H., & Benartzi, S. (2004). Save More Tomorrow™: Using Behavioral Economics to Increase Employee Saving. *Journal of Political Economy, 112,* S164-S187. https://doi.org/10.1086/380085

Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases. *Science, 185,* 1124-1131. https://doi.org/10.1126/science.185.4157.1124

Tversky, A., & Kahneman, D. (Eds.). (2000). *Choices, Values, and Frames.* Cambridge University Press, 143. https://doi.org/10.1017/CBO9780511803475.008

Wen, F., Gong, X., Chao, Y., & Chen, X. (2014a). The Effects of Prior Outcomes on Risky Choice: Evidence from the Stock Market. *Mathematical Problems in Engineering, 2014,* Article ID: 272518. https://doi.org/10.1155/2014/272518

Wen, F., He, Z., Dai, Z., & Yang, X. (2014b). Characteristics of Investors? Risk Preference for Stock Markets. *Economic Computation and Economic Cybernetics Studies and Research, 48,* 235-254.

Yuan, F., Sawaya, K. E., Loeffelholz, B. C., & Bauer, M. E. (2005). Land Cover Classification and Change Analysis of the Twin Cities (Minnesota) Metropolitan Area by Multitemporal Landsat Remote Sensing. *Remote Sensing of Environment, 98,* 317-328. https://doi.org/10.1016/j.rse.2005.08.006

Zhang, J., Lai, Y., & Lin, J. (2017). The Day-of-the-Week Effects of Stock Markets in Different Countries. *Finance Research Letters, 20,* 47-62. https://doi.org/10.1016/j.frl.2016.09.006

Zhong, X., & Enke, D. (2019). Predicting the Daily Return Direction of the Stock Market Using Hybrid Machine Learning Algorithms. *Financial Innovation, 5,* 1-20. https://doi.org/10.1186/s40854-019-0138-0