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Research article

Stock returns and calendar anomalies on the London Stock Exchange in the dynamic perspective of the Adaptive Market Hypothesis: A study of FTSE100 & FTSE250 indices over a ten year period

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Abstract: This paper analyses the behaviour of stock returns and calendar anomalies over a ten year period: 2007–2016 on the London Stock Exchange, through two major indices, the FTSE100 and FTSE250. The efficiency of the indices and the presence of calendar anomalies are investigated with parametric and non-parametric tests. The two main indices of the UK stock market undergo changes from states of dependency of returns to independence of returns and vice versa, but their behaviour is not concomitant. This study finds that financial markets in the UK can undergo changes from states of inefficiency moving to efficiency and vice versa in support of the Adaptive Market Hypothesis. This study also captures the inconstant and time varying behaviour of calendar anomalies and their occurrence. This again supports the Adaptive Market Hypothesis. Overall, it enables investors to get a better understanding of the behaviour of stock returns and to devise profitable investment strategies according to market conditions.

Keywords: London Stock Exchange; market efficiency; parametric and non-parametric tests; behavioural finance

JEL Codes: G12, G14, G15

1. Introduction

1.1. Background

According to the Efficient Market hypothesis (EMH), stock prices adjust to new information in efficient markets without delay, eliminating arbitrage opportunities (the realisation of profits without taking additional risk (Malkiel, 2005)). This implies that stock prices change randomly, but over the years, many studies have shown that stock prices do not follow a "Random Walk" and give rise to opportunities for profit (Fama and French, 1988; Lo and MacKinlay, 1988; Brock et al., 1992; Jegadeesh and Titman, 1993; Opong et al., 1999; Lim et al., 2010). As pointed out by Urquhart and Hudson (2013) the majority of these studies evaluated whether the market is efficient or not over the whole period. As market and environmental factors change over time, it can be expected that a "whole period" conclusion is inadequate and there is justification to study sub-periods for more insights.

A new theory called the "Adaptive Market Hypothesis" (AMH), introduced by Andrew Lo in 2004, incorporates previous economic views and conceptualises an evolutionary market which takes into account the Darwinian principles of competition, adaptation, natural selection and survival and also accounts for human irrationalities in decision making. Under this approach, market efficiency is dynamic and can go through different states of efficiency, reverting from efficiency to inefficiency and vice versa depending on environmental factors and market participants' actions. This implies that arbitrage opportunities can appear and disappear over time and investors' success or failure in their strategies depends on the state of evolution of the financial market.

1.2. Research on the AMH

In recent times, some research has been conducted on the AMH. Lim and Brooks (2006) studying the US market find that the degree of market efficiency varies through time in a cyclical fashion. Todea, Ulici and Silaghi (2009) report that returns are not constant over time, but rather episodic. Ito and Sugiyama (2009) studying S&P500 returns show that the degree of market efficiency varies over time. Kim, Shamsuddin, and Lim (2011) find strong evidence that return predictability fluctuates over time in a similar way to that described by Lo (2004) and that the US market has become more efficient after 1980. Smith (2011) investigating European emerging and developed stock markets, finds support for the time-varying nature of return predictability which is consistent with the adaptive market hypothesis. Lim et al. (2013) show that the three largest US indices have time-varying properties and argue that markets must go through periods of efficiency and inefficiency.

1.3. Purpose and aim

The purpose of this paper is to extend the literature on the AMH while examining its relevance to the London stock market. Its aim is to examine the weak form efficiency of the London stock market in terms of the EMH and the AMH and then to discuss implications for investors. Of particular interest additionally, is the phenomenon of "Calendar Anomalies", which refers to the predictable occurrence of anomalous returns in some part of the calendar year. In addition to the testing of predictability of returns, well known Calendar anomalies such as the Monday effect, the January effect, the turn-of-the-month effect and the Halloween effect are researched in this paper.

The time period chosen for this study is 2007–2017 which include the years of the Global Financial Crisis (2008–2009) and also the beginning of uncertainty in the UK economy resultant from the results of the Brexit Referendum (June 2016). The analysis is conducted in three parts: in the first part, the efficiency of the indices are investigated under the classic EMH with parametric and non-parametric tests; in the second part the daily sample is divided into five sub-samples and the efficiency/inefficiency of each sub-sample is tested under the EMH and the AMH; in the third part Calendar anomalies are analysed in line with an AMH approach.

1.4. Research contribution

The concept of the AMH (Andrew Lo, 2004) is an advancement over the traditional EMH (formulated by Fama (1970)). While the EMH analysis is a static one, simply classifying a market as efficient or not; the AMH, through sub-period analysis, is able to identify the dynamics of changes in efficiency from inefficiency to efficiency and vice versa ie from non-predictability of returns to predictability of returns and vice versa. These dynamics in changes in market efficiency can contribute to understanding the impact of external events such as changes in investor confidence, uncertainties, crises in stock markets. The FTSE100 and FTSE250 indices are constituted from the top 350 stocks by market capitalisation on the London Stock Exchange. There are no previous tests of the FTSE100 and FTSE250 indices on the London stock market in terms of the AMH. The impact of the global financial crisis (2008–2009) and the Brexit Referendum (2016) are evaluated. The current research thus extends the available literature on market efficiency on the London Stock Exchange in terms of return predictability and the existence of Calendar anomalies over different sub-periods and events using parametric and non-parametric tests and supports the concept of the AMH, as a superior conceptualization of market efficiency over the EMH.

1.5. Structure of the paper

In the first section, the aim and overview of the research were provided. Section Two is a review of relevant literature. This part presents a critical review of the most relevant articles on the subject of this research. Section Three explains the design of the research, methodological choices made and data sources. Section Four presents the results of the analysis conducted with interpretations and discussions while in Section Five, the conclusions of the research and recommendations for future research are presented.

2. Literature review

When speaking about efficiency in the stock market, the idea that investors make rational decisions based on available information is a very common assumption. However, Behavioural Finance has identified many forms of cognitive bias that make investors irrational and it has been also been demonstrated that inefficiencies do exist over time and efficiency in the market should not be considered as a "final destination" but more as a "phase" among phases. And it is from this belief that the concept of an "Adaptive Market Hypothesis" has been formulated: as stock market returns appear to go through phases of dependence and independence, individuals must adapt their investment strategies if they want to profit from each phase. Whoever is able to follow the market behaviour will "survive", otherwise will be replaced. And this idea is not so modern as it seems: the famous economist Keynes in the 1930s allegedly said that "Markets can stay irrational longer than you can stay solvent" meaning that investors should base their decision on market behaviour and adapt to it if they want to be successful. To gain a better comprehension of how this concept has evolved during the years, in the next sub-sections the Efficient Market Hypothesis is firstly presented together with its critiques and, finally, the Adaptive Market Hypothesis is explained and examined through its founder's own work. Studies based on this theory are also reported. Lastly, the four Calendar anomalies covered in this research are described, alongside main research in this area.

2.1. The Efficient Market Hypothesis (EMH)

The Efficient Market Hypothesis was first suggested by Samuelson (1965) in his article "Proof that Properly anticipated Prices Fluctuate Randomly", and then developed by Fama in 1970. This theory (Fama, 1970) is founded on the idea that in an efficient market, "the prices (of shares) fully reflect all the available information" and that market efficiency is created by a large number of market participants, with the intent of exploiting even the smallest information to gain some profit, and without knowing it, remove that profit by introducing the information in the market. The EMH was also brought to an extreme with the "neoclassical" idea that prices cannot be forecast. The belief that there is rationality in all the investors was firstly proposed in 1978 by Lucas, while other academics, such as Leroy (1973), Rubinstein (1976) and Breeden (1979) theorized an equilibrium between demand and supply in the market "where individuals and corporations act rationally to optimize their own welfare" (Lo, 2004). There are three types of efficiency: strong-form, semi-strong and weak-form market efficiency. The weak-form efficiency is so far the most commonly tested and asserts that prices already reflect all information which can be derived by examining historical price data and therefore neither can security prices be predicted nor arbitrage strategies be devised. Moreover, there are some conditions for market efficiency that Fama (1970) provides: (i) no transaction costs in trading securities, (ii) all available information is costlessly available to all market participants, and (iii) all agree on the implications of current information for the current price and distributions of future prices of each security.

2.2. The behavioural finance critiques

Many scholars, predominantly psychologists and experimental economists, criticized the EMH idea that market participants are rational and demonstrated that irrationality is usually present when making investment decision and that behavioural biases (such as overconfidence, overreaction, loss aversion) are very common among investors. The behaviouralists, namely the supporters of this psychology-based theory called Behavioural Finance, affirm that "quantitative models of efficient markets are likely to be wrong" (Lo, 2004) and that, under uncertainty, investors tend to base their decisions on emotions. Grossman and Stiglitz (1980) also argued that if the market was efficient, then there would be no motivation in trading and markets would vanish.

2.3. The Adaptive Market Hypothesis (AMH)

Academics supportive of the EMH simply argued that a few inefficiencies could be present sometimes in the market, however, investors could not benefit from them in the long term as most of the arbitrage opportunities would disappear very quickly. Andrew Lo, by taking into considerations all the critiques and praises of the EMH, decided to compare the characteristics of two disciplines, Psychology and Economics, which were at the base of two opposite points of views (on one side, the one that was against the EMH and on the other side the one that was supportive of it). He discovered that Psychology was founded on observation and experimentation, while Economics on theory and abstraction (Lo, 2004): this diversity was the simple reason why the EMH supporters and opponents could not find a meeting point. Lo considered the work of Samuelson(1947), "Foundation of Economics Analysis" which is the groundwork of many economic postulates that are used even today by academics, as one of the causes for an "apparent" inconsistency between the EMH and the empirical findings of Behavioural Finance. In fact, according to Lo and MacKinlay (1999), the data should not be analysed "through the filtered lenses of classical market efficiency" (Lo and MacKinlay, 1999), and that a purely deductive approach is not always appropriate for economic analysis: in fact, while, in Physics, a study based on a few postulates is very successful because the interactions are analysed between inanimate objects, in the economic environment, there are a complex number of human interactions and it is very difficult to model the behaviour of many individuals especially because the way they act is "heuristic, adaptive and not completely predictable" (Lo, 2004).

Consequently, Lo (2004), inspired by the idea of an "evolutionary psychology" (which was proposed for the first time by Wilson (1975)) where the principles of competition, reproduction and natural selection are applied to social interactions to account for some characteristics of human behaviour, was able to reconcile the EMH with Behavioural Finance, by elaborating a new thesis: the "Adaptive Market Hypothesis". The idea of revolution is applied to financial settings and the belief that "individuals maximize expected utility and have rational expectations" (Lo, 2004) is charged to the idea of "survival" through natural selection. Indeed, according to the AMH, "prices reflect all the information derived by the combination of environmental conditions and the number and nature of "species" in the economy" (Lo, 2004). The "species" in the economy correspond to groups of market participants such as pension funds, hedge-fund managers and retail investors, each of them characterized by a unique behaviour. If there are many species that compete for scarce resources (namely profit opportunities) in a single market, then that market is going to be very efficient. On the other hand, if a small number of species are competing for a large amount of resources, then that market will be less efficient.

According to this view, market efficiency is dynamic, and is highly correlated to the way market participants adapt to the continuous changes in the financial ecosystem. In fact, under the AMH, the economy can be seen as a never ending cycle with a high level of competition in the market, caused by a decrease in resources or an increase in the population, triggering an additional reduction in the number of means and, as a natural consequence, the population is downsized, which, again, lessens the level of competition and generates a new cycle. Consequently, the evolving market conditions, together with the size of the population and its ability to survive during market shifts, determine whether investment strategies are profitable or not. During these market cycles, in fact, only the "fittest traders" will be able to survive and be rewarded; the unfit ones will be simply eliminated from "the population" after several losses.

There are a few practical implications of this theory: first, the relation between risk and reward, is not constant across periods. Any modification in the market, such as a change in tax laws, dramatically affects that payoff. Moreover, "natural selection" selects which species of market participants can trade on the market. As an example of "natural selection," Lo (2004) cites those investors who suffered huge losses during the dotcom bubble at the beginning of 2000 who have most probably left that market, due to the high losses, and new investors have arrived to invest in it. As a result, it is evident that history is a very important measure of the present, as the past events still influence the present prices and the risk that market participants are willing to take. A further implication is that arbitrage opportunities are present in the market. According to the viewpoint of an evolution of the market, new opportunities are frequently generated by the constant variation of species that follows a cycle of birth and death and by the modifications in the market and organisations. In contradiction of the assumption of the EMH, the market does not linearly tend to a superior level of efficiency over time but, in reality, it follows a dynamic behaviour "with cycles as well as trends, bubbles, crashes, and other phenomena that are routinely witnessed in natural market ecologies" (Lo, 2004).

A further implication is that investments strategies can be appropriate and profitable in certain environments while be inopportune in others. This means that, under AMH, returns from arbitrage strategies may decline for a time, but return to generate profits when the conditions change and are more favourable for those types of trades. Therefore, it is vital to identify each phase of the economic cycle and use the correct strategies to take advantage from different market opportunities. From figure 1 below, it is observable that the degree of efficiency in the UK market moves within cycles and it is not, as the EMH suggests, in a permanent equilibrium. The final implication is that innovation is the only possibility of survival: as the risk/reward relation varies across time and market conditions change together with the types of market participants, investors must be ready to rapidly adapt to different market conditions if they want to survive during the natural selection process. Their ability to own a multiplicity of capabilities, such as the understanding of financial technology (for example, Fintech), is fundamental to increase the chances of survival. At the end of his paper, Lo (2004) admits that his evolutionary theory which covers Darwinian principles, including "survival of the fittest" will take time to get academic recognition.

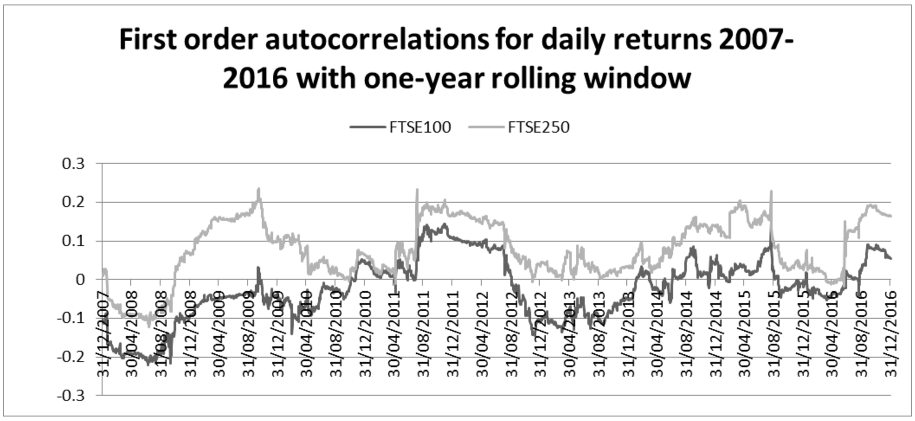

Figure 1. First order autocorrelation coefficients for daily returns of the FTSE100 and FTSE250 indices using one year rolling window from January 2007 to December 2016. Source: Authors'work.

In support of this new theory by Lo (2004), many academics recently decided to test whether the AMH can describe market efficiency better than the EMH. Among others, Lim and Brooks (2006) study the changing market efficiency in developed and emerging stock markets by using a rolling sample approach and notice that there are constant cycles in the market efficiency and therefore that the AMH can actually examine the market behaviour in a more analytical way than the EMH. Kim et al. (2011) in their paper, investigate the stock predictability of daily DJIA data from 1990 to 2009 and, with the employment of sub-samples, support the assumption of a time-changing dependability of returns linked to market conditions: during market crashes the return dependence is low, instead, during political crises and periods of mild economic uncertainty, there is a high degree of return predictability. Another research paper by Charles, Darné, and Kim (2012) on return predictability of fifteen European emerging stock markets and three developed markets shows that return dependence is different according to each market and that, during the Global Financial Market crisis in 2008–2009, there was a high return predictability in some countries (included UK). In a paper on the study of efficiency in three major stock markets(US, UK, Japan), Urquhart and Hudson (2013) found that the AMH is a better theory than the EMH by using parametric and non-parametric tests to check whether efficiency is present over very long-run historic data. In another study by Manahov and Hudson (2014) the AMH is also examined in artificial markets and the results show evidence that stock market dynamics are coherent with the concept of evolution conjectured by the AMH. This result is also supported by Boya (2019) on the French Stock Exchange. In another paper by Urquhart and McGroarty (2014), they observe, through the use of sub-sample analysis, how calendar anomalies behave over time, and the results support the AMH with the evidence that some of them are only present under certain market conditions. This result is also supported by work on calendar anomalies on the Pakistan Stock Exchange (Shahid and Sattar, 2019). More studies on the specific calendar anomalies which are going to be examined in this paper are reported in detail in the next sub-section. Overall, the literature about the AMH is rising every year, however, Lo (2004) affirmed on his own paper, that every new hypothesis needs time to be accepted and it will take a while to see the AMH recognised as a new (and, probably, more efficient) way of analysing financial markets.

2.4. Calendar anomalies

Some common calendar anomalies which will be examined in this research are: “The Monday effect,” “The January effect,” “The Turn-of-the-month-effect” and “The Halloween effect.”

2.4.1. The Monday effect

This anomaly is also called the Weekend effect*:* an anomaly in the stock markets in which the returns on Monday are considerably lower than those on the previous Friday. This is probably one of the most documented effects and it was known since 1920s. The first to acknowledge it was Kelly (1930) who discovered that Monday was the worst day to buy stocks, according to an analysis of stocks returns over a three-year period. The first academic article that reported this effect was that of Cross (1973), who analysed the behaviour of the S&P 500 returns during a seventeen years period and discovered that the mean on Mondays was −0.18% while the mean on Fridays was of 0.12% and that there was a strong relationship between Monday returns and the previous Friday returns. French (1980) also discovered that US stock returns had negative and statistically significant Monday returns. Many studies confirmed this evidence: for example, Keim (1987) and Lakonishok and Smidt (1988) studied the US indexes for long periods of time and reported negative Monday returns in all the sub-sample windows. Recently, however, the effect's strength is diminishing: for example, Connolly (1989) found out that after 1974 the effect was not significant anymore but remained negative in sign. Other studies, like Mehdian and Perry (2001), revealed that there was a reversal in Monday returns for large US stocks between 1987 and 1998, but yet there were persistent negative returns in small stocks. Doyle and Chen (2009), after the examination of 11 major stock markets, concluded that returns behaviour during the week is very sensitive to the sub-sample used in the analysis. Urquhart and McGroarty (2014) report that the Monday effect fluctuates over time with some sub-periods exhibiting positive coefficients and others negative coefficients. As these anomalies are not constant over time throughout the whole sample, Urquhart and McGroarty (2014) concluded that this behaviour supports the AMH.

2.4.2. The January effect

This is an anomaly related to a seasonal increase in stock prices during the month of January. It was reported for the first time in 1976 by Rozeff and Kinney (1976) whose study showed that the average return in January was 3.48% compared to the 0.42% during other months. Roll (1983) and Reinganum (1983) supported the idea that the January effect is more present in small firms. Kato and Schallheim (1995), while studying this effect in the Tokyo Stock Exchange, also found a strong relationship between return and size. However, Kohers and Kohli (1991) rejected this hypothesis. Gultekin and Gultekin (1983) attributed the higher returns to the turn of the tax year. Recently, the January effect has declined: Riepe (1998) attributed this decrease to the emergence of futures contracts as investors could profit from the effect in a cheaper way. Gu (2003) demonstrated that both small and large firm returns in Russell indices decreased since 1988 and disappeared since then. Moller and Zilca (2008) argued that, between 1927 and 2004, in NYSE, AMEX and NASDAQ, the January effect did not disappear but that abnormal returns were always present (either higher or lower). According to Jacobsen and Zhang (2013), UK stocks returns do not exhibit the January effect since 1830 when Christmas became a public holiday. Urquhart and McGroarty (2014) report that the January effect fluctuates over time, with some sub-periods being positive and some others being negative, with a bi-directional behaviour in support of the AMH.

2.4.3. The Turn-of-the-month-effect

This is an anomaly based on the discovery that the last day of the month and the first three trading days of the following month (TOTM) have a higher rate of return. It was first found by Ariel (1987) in the US stock market. Lakonishok and Smidt (1988) also discovered that from 1897 to 1986 DJIA returns were 0.475% during TOTM days compared to 0.061% during non-TOTM days. McConnell and Xu (2008) confirmed this result and, moreover, by extending the sample period up to 2005, demonstrated that the effect in DJIA returns was still present. Atanasova and Hudson (2010) also confirmed that the TOTM effect did not disappear since the study of Lakonishok and Smidt (1988) but that its strength increased over time. Khaled and Keef (2012) analysed the effect in fifty international stock indices between 1994 and 2006 and found out that it was present in all of them. Urquhart and McGroarty (2014) suggest that the TOTM effect is also present in all the sub-samples, but its strength was changing over time.

2.4.4. The Halloween effect

This is an anomaly based on the idea that stocks perform better between October 31 and May 1 than during the period from the beginning of May to the end of October. It was first discovered by Bouman and Jacobsen (2002) who demonstrated that the effect was present in thirty-six out of thirty-seven equity markets investigated from 1970 to 1998. Lucey and Zhao (2008), while analysing this effect in US CRSP data, found out that it may just be a reflection of the January effect. In a later study Haggard and White (2010) found that an investment in a Halloween portfolio provides “risk-adjusted” returns greater than the buy-and-hold strategy, even after considering transaction costs. Andrade, Chhaochharia and Fuerst (2013) extended a study by Bouman and Jacobsen (2002) from 1998 to 2012, and concluded that between November and April the returns are significantly higher than during the rest of the year.

2.5. Summary

Based on the findings in current literature, the AMH has been found to be a more logical and organic approach to study for market efficiency over time. In fact, many studies show that “AMH provides a better description of the behaviour of stock returns than the classic EMH” (Urquhart and Hudson, 2013). Further Urquhart and F. McGroarty (2014), who examined calendar anomalies in the DJIA find support for the hypothesis of a continuous “evolving” market efficiency in accordance with the AMH. Furthermore, in the same study, the presence of certain anomalies have been observed only during specific market conditions and this suggests the idea that arbitrage opportunities exist but simply change depending on the economic environment. This research tests whether there is support for the idea of a dynamic market efficiency in a developed economy (specifically the UK), and to check whether arbitrage opportunities such as calendar anomalies are present and influenced by changes in the market conditions.

3. Research design

The aim of this study is to examine the weak form efficiency of the London stock market in terms of the EMH and the AMH and then to discuss implications for market participants. Given the existing literature on the EMH and the AMH, this study is based on the positivist style with a deductive approach and application of quantitative methods. The positivist feature of this method incorporates the selection and examination of the relationships between variables. As such, this research is based on statistical inference on numerical parameters to obtain value free results. The objectives of this study are, firstly, to test whether the London Stock Market main indexes (FTSE 100 and FTSE250) are efficient by following tests for the Efficient Market Hypothesis and the Adaptive Market Hypothesis, and secondly to check if Calendar anomalies are present. A range of tests will be applied according to past studies on EMH and AMH.

In the next sections, the methodology, sources of data and sample selection are discussed.

3.1. Methodology

In the weak form of the EMH, the market follows a random walk and prices are not predictable: ie a value in such a a series, price, y_t depends only on its previous value and a random disturbance term ε at time t. This can be expressed as

$$y_t = y_{t-1} + \varepsilon_t \tag{1}$$

The first difference of a random walk is termed as a stationary series, as it comprises only the random disturbance term. Consequently testing for the weak form of the EMH centres around random walk and stationarity. The AMH, however conceptualises market efficiency with a dynamic perspective: one which shifts from a state where returns are dependent to one in which they are not and so on; ie evolving according to the outlook and behaviour of the underlying participants.

After ascertaining the descriptive statistics of the data (mean, median, standard deviation, skewness, kurtosis and normality), a two part analysis will be conducted.

(i) in the first part of the analysis, a range of tests for assessing weak form efficiency are carried out using a mix of parametric and non-parametric tests: for assessing whether the series is stationary, the Augmented Dickey Fuller (ADF) test, the Phillips Perron (PP) test and the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test are applied. If stationarity is not seen at the level, then differences will be tested.

The ADF test is a parametric test for higher order correlation by assuming that the series (y) follows an AR(p) process with p lagged difference terms and an error term $v_{t.}$ Under the null, the series is assumed not to have a Unit Root.

$$y_t = \alpha y_{t-1} + x'\delta + \beta_1 \Delta y_{t-1} + \beta_2 \Delta y_{t-2+} \ldots + \beta_p \Delta y_{t-p} + \nu_t \tag{2}$$

The Phillips Perron test (1988) is an alternative way of checking for a Unit Root and uses a non-parametric method of controlling for serial correlation. Under the null the series is assumed not to have a Unit Root.

The KPSS test, is a non-parametric test and unlike other tests assumes stationarity under the null and is based on the residuals from the OLS regression of yt on the exogenous variables x'_t; u_t is the error term and δ is the coefficient of x'_t:

$$y_t = x'\delta + \mu_t \tag{3}$$

As the null in the KPSS tests is framed from an opposite perspective, all three tests are conducted on the price series for additional confirmation. (i) Autocorrelation analysis uses a parametric test to measure the correlation coefficient between a series and lagged values in the same series. A positive autocorrelation implies that present values are dependent on past values and a negative autocorrelation indicates the existence of a reversal in the movements. A return series is truly random when it has a zero-autocorrelation coefficient. The auto-correlation coefficient τ_k of a series Y at k lags is estimated as,

$$\tau_k = \sum_{t=k+1}^{T} (Y_t - \bar{Y})(Y_{t-k} - \bar{Y}) / \sum_{t=1}^{T} (Y_t - \bar{Y})^2 \tag{4}$$

where $\bar{Y}$ is the mean of the series. The acceptance or rejection of the null hypothesis is computed through the Lyung Box Q-statistic, which at lag k is computed as

$$Q_{LB} = T(T+2)\sum_{j=1}^{k}\frac{{\tau_j}^2}{T-J} \tag{5}$$

where τ_j is the j-th autocorrelation and T is the number of observations. The Q-statistic is asymptotically distributed as a x^2 with degrees of freedom equal to the number of autocorrelations. The Variance Ratio test is a parametric test devised by Lo and Mackinlay (1988), to test whether values are serially uncorrelated. If a stock price follows a random walk, then the variance of the k-period difference is equal to k times the variance of the one period variance. If r_t is the asset return at time t, where t = 1,2,3…T. The variance ratio for r_t with holding periods k is

$$VR(k) = {\sigma_k}^2 / \, k\sigma^2 \tag{6}$$

where ${\sigma_k}^2$ is the variance of k-period return. Under the null hypothesis, the variance ratio equals 1 for all ks since returns are serially uncorrelated with $\rho(j) = 0,$ where $\rho(j)$ is the autocorrelation of r_t of order j. When estimating *VR(k)*, the value of holding periods must be chosen. In the literature, the variance ratio is typically studied at holding periods of 2, 4, 8 and 16 and this format will be also used in the current analysis.

The BDS test (Brock et al., 1987), is a non-parametric test to test for serial dependence or non-linear structure in a series. Under the null hypothesis, the series being tested is random. Residuals from a regression can be tested for mon-linearity. It uses the correlation dimension of Grassberger and Procaccia (1983) and requires the specification of a distance between points, and the number of consecutive points in a data set, called the embedding dimension (m). It is usually conducted at a distance of 0.5–2 standard deviations, with the embedding dimension taking values between 2 to 10.

(ii) in the second part of the analysis, data is tested for the presence of some common Calendar anomalies outlined in the literature review section (“The Monday effect”, “The January effect”, “The Turn-of-the-month-effect” and “The Halloween effect”.) using two alternative methods. In the first method, the following regression equation is estimated to examine the behaviour of calendar anomalies over time:

$$R_t = c + \beta D_t + \varepsilon_t \tag{7}$$

where R_t is the return on the stock index, D_t is the calendar effect indicator, ε_t is the error term and t is the time of observations. As the present research is also concerned with the time-varying properties of stock returns estimation with a GARCH (p, q) model is preferred over the standard OLS version.as these models allow variance to be expressed as conditional on the past variance and error rather than invariant through the series. Previous research shows that the GARCH (1, 1) model is a robust version of this family of models for estimating volatility (Engle, 2001)and this model is applied in the current research. The mean equation is the same as (7) above and the variance equation is:

$$h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \theta h_{t-1} \tag{8}$$

where h_t and h_{t-1} are the conditional variance of the stock returns at time t and t-1, while α_0 , α_1 *and* θ are the GARCH model coefficients.

Finally, as the GARCH model does not capture the non-normality of the data, a non-parametric test, the Kruskal-Wallis test, is employed to observe the differences between the returns on calendar effect days and on non-calendar effect days. The formula of this test is

$$H = \left(\frac{12}{N(N+1)}\sum_{j=1}^{k}\frac{R_j^2}{n_j}\right) - 3(N+1) \tag{9}$$

where R_j^2 is the average rank of observations in the jth group, n_j is the total number of observations in the jth group, k is the number of groups and N is the total number of observations.

3.2. Data

The Data of this study is sourced from Bloomberg Terminal and consists of daily closing prices for the ten year period 2007–2016. The full samples are further broken up into five sub samples each of two years. The decision to analyse this decade is due to the considerable changes in the Market during those years and two major events in these years: the Global Financial Crisis and the Brexit referendum decision.

3.3. Selection of sample

Two indices have been chosen for this study: FTSE 100 and FTSE 250; the first is a value weighted share index of the top hundred companies listed on the London Stock Exchange by market capitalisation, whilst the second is similarly constructed and consisting of the 101st to the 350th largest companies listed on the London Stock Exchange. These two indices can be found combined into one index, the FTSE 350, however, in this study, a separate analysis of the two has been judged to be more appropriate as the indices represent companies quoted on the London Stock Exchange under different perspectives: while the FTSE 100 is composed largely of internationally focused companies they are exposed to the exchanges rates of the Pound sterling in the Global Economy as a whole, while the FTSE250 contains a smaller percentage of international companies and is a better indicator of the UK domestic economy. Finally, in terms of Capital Market theory, the selection of value weighted indices for research are more representative of the underlying market than other forms of index construction.

4. Analysis and findings

4.1. Graphic plots of the data

Plots of the two indices over the entire ten year period (2007–2016) are as below.

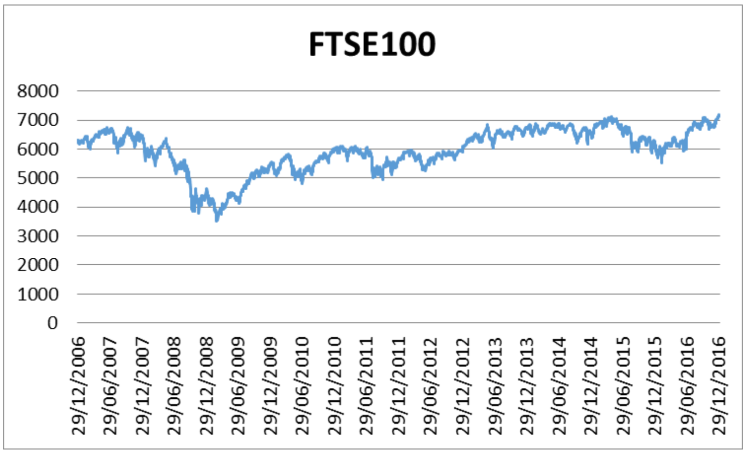

Figure 2. FTSE100 daily closing prices from 2007 to 2017. ((i) FTSE 100). Source: Authors' work.

Figure 2, is a graph of the daily closing prices of the FTSE 100 from January 2007 to January 2017. From the graph it is possible to see that the stock prices of FTSE100 were falling during the period of 2007–2008 as a consequence of the Global Financial Crisis, then rising back in 2009 and mainly moving upwards up to the end of 2015; then falling again in the middle of 2016 and rising again after that. In this ten year period the highest value of the index was 7178 on the 31st of January 2017 and the lowest one was of 3513 on the 3rd March 2009. The pattern is quite unstable, and it doesn't seem to follow a particular trend.

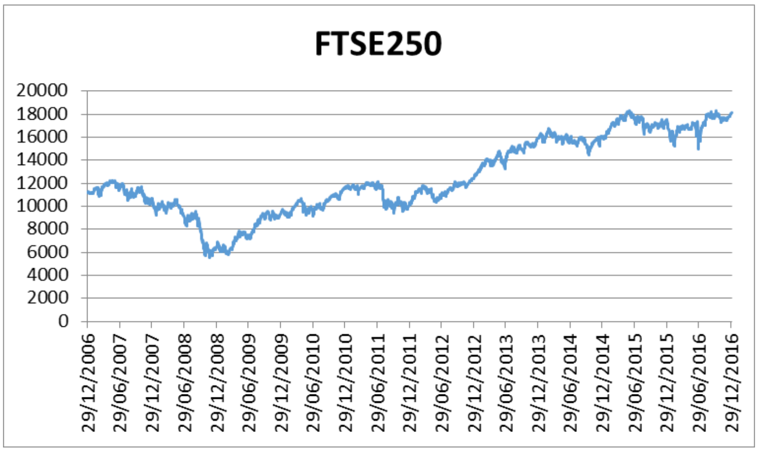

Figure 3. FTSE250 daily closing prices from 2007 to 2017. ((ii) FTSE 250). Source: Authors' work.

Figure 3, is a graph of the daily closing prices of the FTSE 250 from January 2007 to January 2017. From the graph, it is possible to observe that the pattern of the FTSE250 closing prices is very similar to the one of the FTSE100. During the ten year period, the highest value of the index was 18342 on the 4th of October 2016 and the lowest value was 5578 on the 20th of November 2008.

4.2. Descriptive statistics

The descriptive statistics of returns on the two indices over the whole ten year period of the study and in the two year sub-samples, are presented in Tables 1 and 2 below (details in Appendix A).

The total number of observations over the whole period 2007–2016 are 2529: over the entire period, the mean and median return of both samples (FTSE100 and FTSE250) was positive; with a distribution which was negatively skewed and leptokurtic. The mean return of the FTSE250 was higher, but the volatility was about the same.

Table 1. Descriptive statistics of returns on FTSE100 and FTSE250 over the period 2007–2016. (i) Full periods (2007–2016).

Full sample	Obs	Mean	Median	Maximum	Minimum	Std Dev	Skewness	Kurtosis	JB stat
FTSE100	2529	5.66E-05	0.0004	0.0938	−0.0927	0.0127	−0.1218	10.0413	5230.731
FTSE250	2529	0.000191	0.0007	0.0746	−0.0746	0.0122	−0.4084	6.9499	1714.35

Table 2. Descriptive statistics of returns for all sub-samples in FTSE100 and FTSE250. (ii) Sub samples (two year periods).

Sample	Obs	Mean	Median	Maximum	Minimum	Std Dev	Skewness	Kurtosis	JB stat
FTSE100									
2007–2008	508	−0.000611	−0.000129	0.093843	−0.092656	0.018440	0.006821	8.785217	708.4256
2009–2010	506	0.000564	0.000861	0.050322	−0.054805	0.012994	−0.120523	4.888717	76.4345
2011–2012	500	0.000039	0.000033	0.039429	−0.047792	0.011268	−0.231748	4.810113	72.7362
2013–2014	506	0.000193	0.000649	0.030323	−0.030272	0.007417	−0.266822	4.728781	69.0156
2015–2016	506	0.000139	0.000609	0.035150	0.047795	0.010710	−0.132721	4.593860	55.0454
FTSE250									
2007–2008	508	−0.001029	−0.000184	0.074621	−0.067348	0.016842	−0.109652	5.072236	91.91108
2009–2010	507	0.001206	0.001766	0.052622	−0.042374	0.013252	−0.125294	3.942866	20.10657
2011–2012	503	0.000125	0.000586	0.032971	−0.050353	0.011199	−0.492214	4.695460	80.55718
2013–2014	503	0.000495	0.000860	0.024859	−0.026419	0.007617	−0.275825	3.674521	15.88863
2015–2016	500	0.000214	0.000500	0.035132	−0.074565	0.010019	−1.488243	15.088720	3229.096

The observations for each sub-sample range from 500 to 508 due to differences among the dates of each year. In both indexes, the lowest mean is reported in the first sub-sample (2007–2008) while the highest one in the second sub-sample (2009–2010). The highest volatility is present in the first sub-sample for both series. All logged daily returns are left skewed except for the FTSE100 in the first sub-sample which is positively skewed. The Kurtosis is higher during the period 2007–2008 for the FTSE100 and during the period 2015–2016 for the FTSE250. This observation is very significant because it demonstrates how the FTSE100 returns are more linked to the global economy's condition (the 2008 Financial Crisis) while the FTSE250 returns are much more influenced by the UK economy (Brexit Referendum). From the J-B tests we can conclude that both the full samples and all the two years sample periods are not normally distributed.

4.3. Data analysis and findings

In this section, the results of the tests conducted on the data of the FTSE100 and FTSE index price series for full sample and subsamples of two years as discussed in the methodology section, are presented.

4.3.1. Unit Root tests

The results of the ADF, PP and KPSS tests are as below:

FTSE100: The FTSE100 price series shows stationarity at the first difference for the full sample and the sub-samples (non-stationary at the level for all series). The summary of tests on the FTSE100 and FTSE 250 are presented in Tables 3 and 4 below (details in Appendix B).

FTSE250: The FTSE 250 price series shows stationarity at the first difference for the full sample and the sub-samples (non-stationary at the level for all series).

The tests for a unit root on the FTSE100 and FTSE250, all reject the presence of a unit root at the first difference.

Table 3. Summary of tests for unit root on FTSE100 for whole and sub samples.

Series	Period	ADF*	PP*	KPSS**
FTSE100 full	2007–2016	−51.7448(a)	−52.1233(a)	0.1082(s)
FTSE100ss1	2007–2008	−24.9746(a)	−25.4972(a)	0.1517(s)
FTSE100ss2	2009–2010	−22.89138(a)	−22.89161(a)	0.0710(s)
FTSE100ss3	2011–2012	−21.47349(a)	−21.70468(a)	0.0879(s)
FTSE100ss4	2013–2014	−22.70237(a)	−22.7027(a)	0.1336(s)
FTSE100ss5	2015–2016	−21.6745(a)	−22.1554(a)	0.1920(s)

Note: *ADF and PP statistics: (a) represents significance at the 1% level;

**KPSS: (s) represents that the null of stationarity cannot be rejected.

Table 4. Summary of tests for unit root on FTSE100 for whole and sub samples.

Series	Period	ADF*	PP*	KPSS**
FTSE250 full	2007–2016	−36.0387(a)	−46.0615(a)	0.2145(s)
FTSE250ss1	2007–2008	−22.1108(a)	−22.1098(a)	0.1855(s)
FTSE250ss2	2009–2010	−20.9517(a)	−20.9141(a)	0.0455(s)
FTSE250ss3	2011–2012	−19.6785(a)	−19.5191(a)	0.1935(s)
FTSE250ss4	2013–2014	−20.6135(a)	−20.5667(a)	0.1716(s)
FTSE250ss5	2015–2016	−14.6985(a)	−22.7501(a)	0.1061(s)

Note: *ADF and PP statistics: (a) represents significance at the 1% level.

**KPSS: (s) represents that the null of stationarity cannot be rejected.

4.3.2. Autocorrelation tests

Next autocorrelation tests are performed to test for dependence to arrive at conclusions on randomness. The results of the autocorrelation tests on returns of the two series, FTSE100 and FTSE250 for full and sub-samples are presented in Tables 5 and 6 below (details in Appendix C).

For the FTSE100 returns, in the entire period (2007–2016), there is no autocorrelation at the first lag, though there is significant autocorrelation at the 5% level at the third and fifth lags. There is evidence of autocorrelation in the first (2007–2008), fourth (2013–2014) and fifth (2015–2016) sub-samples, but the second (2009–2010) and third (2011–2012) sub-samples are free of significant autocorrelation at upto five lags. Thus while there is support for non-predictability and the weak form of the efficient market hypothesis for the FTSE100 in the second and third sub-samples, there is support for the alternative hypothesis of market inefficiency and predictability in the first, fourth and fifth sub-samples.

Table 5. Summary of autocorrelation test for FTSE100 for whole and sub samples. (FTSE100).

		Autocorrelation		
Series	Period	1 lag	3 lags	5 lags
FTSE100 full	2007–2016	−0.0290	−0.0340(b)	−0.0470(b)
FTSE100ss1	2007–2008	−0.1060(b)	−0.0950(a)	−0.0850(a)
FTSE100ss2	2009–2010	−0.0180	−0.0350	−0.0100
FTSE100ss3	2011–2012	0.0400	−0.0830	−0.0030
FTSE100ss4	2013–2014	−0.0040	0.1280(b)	−0.0140(b)
FTSE100ss5	2015–2016	0.0350	0.0360	−0.0610(b)

Note: (a) represents significance at 1% level.
(b) represents significance at 5% level.

Table 6. Summary of autocorrelation test for FTSE250 for whole and sub samples. (FTSE250).

		Autocorrelation		
Series	Period	1 lag	3 lags	5 lags
FTSE250 full	2007–2016	0.0870(a)	−0.0360(a)	−0.0700(a)
FTSE250ss1	2007–2008	0.0140	−0.0720	−0.0250
FTSE250ss2	2009–2010	0.0720	−0.0390	−0.0650
FTSE250ss3	2011–2012	0.1250(a)	−0.0780(a)	−0.0400(b)
FTSE250ss4	2013–2014	0.0890(b)	0.0330	−0.0360(c)
FTSE250ss5	2015–2016	0.1240(a)	−0.0240(a)	−0.1530(a)

Note: (a) represents significance at 1% level.
(b) represents significance at 5% level.
(c) represents significance at 10% level.

For the FTSE250 returns, in the entire period (2007–2016), there is significant autocorrelation at the first and fifth lags, at the 1% level. There is evidence of significant autocorrelation in the third (2011–2012), fourth (2013–2014) and fifth (2015–2016) sub-samples at different levels and lags, but the first (2007–2008) and second (2009–2010) sub-samples are free of significant autocorrelation at upto five lags. Overall, there is support for non-predictability and the weak form of the efficient market hypothesis for the FTSE250 in the first and second sub-samples, with this test. Again, while there is support for non-predictability and the weak form of the efficient market hypothesis for the FTSE250 in the first and second sub-samples, there is support for the alternative hypothesis of market inefficiency and predictability in the third, fourth and fifth sub-samples.

While autocorrelation tests show support for a weak form efficient market in the second and third sub samples for the FTSE100, there is support for a weak form efficient market for the

FTSE250 in the first and second sub samples. Both markets show evidence of a market, which switches from in-efficiency to efficiency, and vice versa over the whole period.

4.3.3. Variance Ratio test

If data is assumed to follow a random walk, then the variance of the k-period difference is equal to k times the variance of the one period variance. The Variance ratio test (Lo and MacKinlay, 1988), is typically studied at holding periods (k) of 2, 4, 8 and 16 and this format is also used in the current analysis. Under the null hypothesis, the variance ratio equals 1 for all ks since returns are serially uncorrelated with $\rho(j) = 0$. The summary of tests on the FTSE100 and FTSE 250 are presented in Tables 7 and 8 below (details in Appendix D).

The Variance ratio lest on the FTSE 100 returns over the whole period (2007–2016) supports the hypothesis of a random walk at two periods but not at longer periods (4, 8, 16). For the first sub-sample (2007–2008), there is no support for a random walk for all periods, whilst for the second, third and fourth sub-samples there is support for the hypothesis of a random walk. Finally, in the fifth sub-sample, there is support for a random walk at 2,4 and 8 periods, but not at 16 periods. In all, this is evidence of an inefficient market in the first sub-sample but a weak form efficient market in the second, third and fourth sub-samples, but again reverting to inefficiency in the fifth sub-sample.

The Variance ratio lest on the FTSE250 returns over the whole period (2007–2016) supports the hypothesis of a random walk only at 4 and 8 periods but not at 2 or 16 periods.

For the first sub-sample (2007–2008), there is support for a random walk for all periods, but only at 4,8 and 16 periods for the second (2009–2010), third (2011–2012) and fourth (2013–2014) sub-samples. Finally, in the fifth sub-sample, there is support for a random walk only at 4 periods, but not at 2,8 or 16 periods. In all, this is evidence of an efficient market in the first sub-sample for all periods, but not in the other sub-samples.

Variance ratio tests support the hypothesis of a random walk for the FTSE100 in the second and third sub samples over all lags, for the FTSE250 there is support of a random walk over all lags only for the second subsample. This test supports the hypothesis of a market switching from inefficiency to efficiency and vice versa in the sub-samples and of an adaptive market for the FTSE100 and FTSE250 over the whole sample (2007–2016).

Table 7. Summary of Variance Ratio tests for FTSE100 for whole and sub samples. (FTSE100).

		Variance Ratio*			
Series	Period	K = 2	K = 4	K = 8	K = 16
FTSE100 full	2007–2016	0.9708	0.9013(a)	0.8215(a)	0.7546(a)
FTSE100ss1	2007–2008	0.9036(b)	0.6988(a)	0.5960(a)	0.5785(b)
FTSE100ss2	2009–2010	0.9809	0.9463	0.9645	0.9261
FTSE100ss3	2011–2012	1.0458	0.9883	0.8317	0.6777
FTSE100ss4	2013–2014	0.9881	1.0450	1.0730	1.0380
FTSE100ss5	2015v2016	1.0274	0.9938	0.8356	0.6397(c)

Note: (a) represents significance at 1% level.
(b) represents significance at 5% level.
(c) represents significance at 10% level.

Table 8. Summary of Variance Ratio tests for FTSE250 for whole and sub samples. (FTSE250).

		Variance Ratio*			
Series	Period	K = 2	K = 4	K = 8	K = 16
FTSE250full	2007–2016	1.0867(a)	1.0608	0.9187	0.8540(b)
FTSE250ss1	2007–2008	1.0441	0.9987	0.9750	0.9488
FTSE250ss2	2009–2010	1.0849(c)	1.0747	0.9797	0.8854
FTSE250ss3	2011–2012	1.1123(b)	1.2310	0.9690	0.8590
FTSE250ss4	2013–2014	1.0915(b)	1.1341	1.0754	1.0178
FTSE250ss5	2015–2016	1.1165(a)	1.0262	0.7030(b)	0.5645(b)

Note: (a) represents significance at 1% level.
(b) represents significance at 5% level.
(c) represents significance at 10% level.

4.3.4. BDS test

The BDS test estimates whether there is non linear dependence in the residuals of a regression. Under the null hypothesis, the series being tested is random and the residuals are independent and identically distributed. Referring to the methodology section in this paper it is applied at distances of 0.75σ, 1.5σ and 2σ standard deviations, with the embedding dimensions of 2, 6 and 10. The summary of tests on the FTSE100 and FTSE 250 are presented in Tables 9 and 10 below (details in Appendix E).

For the full sample of FTSE100 (2007–2016), the null hypothesis is rejected at all the tested distances and dimensions. This is also the case for the first sub-sample (2007–2008) and the fourth and fifth sub-samples. The third sub-sample does not reject the null at all tested distances and dimensions.

This supports the hypothesis of a market switching from inefficiency to efficiency and vice versa in the sub-samples and of an adaptive market for the FTSE100 over the whole sample (2007–2016).

Table 9. Summary of BDS tests for FTSE100 for whole and sub samples. (FTSE100).

		BDS test		
Series	Period	m=2	m=6	m=10
		0.75σ	1.5σ	2σ
FTSE100 full	2007–2016	0.0150(a)	0.0728(a)	0.1300(a)
FTSE100ss1	2007–2008	0.2221(a)	0.5149(a)	0.6092(a)
FTSE100ss2	2009–2010	−0.000717	0.0222(a)	0.0560(a)
FTSE100ss3	2011–2012	0.0045	0.0506	0.1036
FTSE100ss4	2013–2014	0.0097(a)	0.0503(a)	0.0779(a)
FTSE100ss5	2015–2016	0.0145(a)	0.0661(a)	0.1140(a)

Note: (a) represents significance at 1% level.
(b) represents significance at 5% level.
(c) represents significance at 10% level.

Table 10. Summary of BDS tests for FTSE250 for whole and sub samples. (FTSE250).

		BDS test		
Series	Period	m = 2	m = 6	m = 10
		0.75σ	1.5σ	2σ
FTSE250full	2007–2016	0.0076(a)	0.0565(a)	0.0988(a)
FTSE250ss1	2007–2008	0.0043(c)	0.0375(a)	0.0746(a)
FTSE250ss2	2009–2010	0.1262(a)	0.3675(a)	0.4481(a)
FTSE250ss3	2011–2012	0.0026	0.0044(a)	0.0812(a)
FTSE250ss4	2013–2014	0.0054(b)	0.0320(a)	0.0431(a)
FTSE250ss5	2015–2016	0.0161(a)	0.0976(a)	0.1642(a)

Note: (a) represents significance at 1% level.

(b) represents significance at 5% level.

(c) represents significance at 10% level.

For the full sample of FTSE250 (2007–2016), the null hypothesis is rejected at all the tested distances and dimensions. This is also the case for the first sub-sample (2007–2008) and the fourth (2013–2014) and fifth (2015–2016) sub-samples. The third sub-sample does not reject the null at 0.75σ and 2 dimensions, but the null is rejected at other tested distances and dimensions.

While the BDS test rejects non linearity in the residuals over all dimensions tested only in the third subsample for the FTSE100, there is no support for non linearity in the residuals for all subsamples for the FTSE250. This supports the hypothesis of a market switching from inefficiency to efficiency and vice versa in the sub-samples and for the FTSE250 over the whole sample (2007–2016).

In summary of the tests for a unit root, autocorrelation, variance constancy and non linearity in the residuals, there is support for weak form efficiency at different periods in the FTSE100 and FTSE250 on the first three tests but on the fourth there is support for randomness of the residuals only in one subsample of the FTSE and none on the other sub samples on the FTSE250. Overall, the market behaviour of switching from efficiency to inefficiency and vice versa in the two markets is evidence of support for the Adaptive Market Hypothesis.

4.4. Calendar anomalies tests on the FTSE100 and FTSE250

As sufficient analysis has already been carried out on the full samples of FTSE100 and FTSE250 (2510 daily observations over the period 2007–2016), these tests are conducted on the sub-samples for greater insights. Following the methodology outlined earlier, GARCH(1,1) estimates are first made for “the Monday effect”, “The January effect”, “The Turn-of-the-month-effect” and “The Halloween effect”. Parameters of the GARCH(1,1) models estimated are stable (α_2, θ are > 0 and significant; (α_2+θ) close to and <1). The significance of the Garch models show heteroscedasticity in the residuals of all the data tested for the FTSE100 and FTSE250.This is followed by an application of the Kruskal-Wallis (KW)test on each sub-sample. The results are summarised below (details are provided in the Appendix F).

Table 11. Summary of Garch(1,1) and KW tests for calendar anomalies on the FTSE100 for whole and sub samples.

Sample period	β	KW statistic
Panel A: Monday effect		
2007–2008	−0.000142	0.269174
2009–2010	0.002981*	4.716422*
2011–2012	−0.001680	4.660537*
2013–2014	−0.000349	0.600467
2015–2016	−0.001099	3.566158*
Panel B-January effect		
2007–2008	−0.000214	0.608794
2009–2010	−0.003662*	4.168928*
2011–2012	0.000352	0.065400
2013–2014	0.000808	0.079734
2015–2016	−0.001063	0.171407
Panel C-TOTM effect		
2007–2008	0.000688	5.188240*
2009–2010	−0.000785	0.009246
2011–2012	0.002608*	2.962647*
2013–2014	0.000192	0.002246
2015–2016	−0.000268	0.000033
Panel D-Halloween effect		
2007–2008	0.000374	0.289127
2009–2010	−0.000564	0.181466
2011–2012	0.000791	0.052595
2013–2014	0.000603	0.377212
2015–2016	−0.000150	0.016560

Note: * represents significance at 5% level.

** represents significance at 10% level.

In Table 11 the results for FTSE100 are reported. Panel A shows that, in the GARCH(1,1) regression, the Monday effect generates a significant positive coefficient only in the second sub-sample. The insignificant negative coefficients in all the other sub-samples suggest that there is a weakening of the effect over time. However, the Kruskal-Wallis test exhibits evidence of the Monday effect in the second, third and fifth sub-samples, consistent with a time-varying behaviour. In Panel B, the January effect is analysed: in the regression there is only one significant coefficient in the second sub-sample, which is confirmed by the Kruskal-Wallis test. None of the other sub-samples generates significant evidence of the effect, however, the coefficients signs change over time and that is still an evidence of the time-varying behaviour. Panel C reports the TOTM effect: only the third sub-sample exhibits a significant positive coefficient in the regression, while the Kruskal-Wallis statistic reports an evidence of the effect in the first and third sub-samples. Panel D shows the results for the Halloween effect: there are no signs of the effect in any of the sub-samples either in the regression or in the Kruskal-Wallis test.

Table 12. Summary of Garch(1,1) and KW tests for calendar anomalies on the FTSE 250 for whole and sub samples.

Sample period	β	KW statistic
Panel A: Monday effect		
2007–2008	−0.001029	0.189447
2009–2010	0.001437	0.683257
2011–2012	−0.002646*	6.275451*
2013–2014	−0.000577	1.476135
2015–2016	−0.001274**	2.944692**
Panel B-January effect		
2007–2008	−0.000079	0.354655
2009–2010	0.001274	1.789928
2011–2012	0.001819	0.767609
2013–2014	0.000521	0.003809
2015–2016	−0.001876	0.423944*
Panel C-TOTM effect		
2007–2008	0.002380	8.404441*
2009–2010	0.000656	0.429317
2011–2012	0.003387*	4.041717*
2013–2014	0.000449	0.228833
2015–2016	0.000155	0.764393
Panel D-Halloween effect		
2007–2008	0.000553	1.183564
2009–2010	0.000478	0.092641
2011–2012	0.000913	1.057977
2013–2014	0.000637	0.395792
2015–2016	0.000191	0.010926

Note: * represents significance at 5% level.

** represents significance at 10% level.

In Table 12 the results for FTSE250 are reported. Panel A shows that in the regression the Monday effect is significant in the second and fifth sub-samples, evidence that is confirmed by the Kruskal-Wallis statistics. Panel B shows January effect results: in the regression estimation there is no sign of significance in the effect, however, the Kruskal-Wallis test exhibits evidence of the effect in the fifth sub-sample. Moreover, the sub-samples produce coefficients that, even if insignificant, fluctuate over time with some periods generating positive coefficients and some periods generating negative coefficients. Panel C shows the TOTM effect results: according to the regression, only the third sub-sample exhibits a significant coefficient, while the Kruskal-Wallis statistics reports significance in the first and third sub-samples. Finally, Panel D presents the Halloween effect analysis: according to the regression and the Kruskal-Wallis test, there is no evidence of this effect in any of the sub-samples and no change in the coefficient signs. To conclude, the FTSE250 sub-samples do not exhibit a strong evidence of any of the Calendar effects, however, Monday effect and January effect coefficient signs do vary over time.

Overall the Monday effect and the January effect occur in different subsamples in the FTSE100 and FTSE250; the TOTM effect happens in both the FTSE100 and FTSE250 in the third subsample, but the Halloween effect is not evidenced in either series over all the sub samples. Also the KW test, a non-parametric test, almost always supports the results of the Garch model. Though strong evidence of any of the effects is not evidenced, the time varying behaviour of their occurrence and the fact that the sub-samples generate significant and insignificant statistics of different signs is supportive of the Adaptive Market Hypothesis.

4.5. Summary of tests

Table 13 and Table 14 below summarise the results of all the tests for the FTSE100 and FTSE250:
(i) Weak form Market efficiency via Random walk

Table 13. Summary-weak form efficiency tests for FTSE100 and FTSE250 for whole and sub samples 2007–2016.

Label	2007–2016	2007–2008	2009–2010	2011–2012	2013–2014	2015–2016
FTSE100						
No Unit Root	√	√	√	√	√	√
No AC			√	√		
Variance Ratio (RW)			√	√	√	
BDS (no NL)				√		
FTSE250						
No Unit Root	√	√	√	√	√	√
No AC		√	√			
Variance Ratio (RW)		√				
BDS (no NL)						

Note: √ Indicates significant evidence; RW: Random walk; NL: Nonlinearity in residuals.

(ii) Calendar anomalies

Table 14. Summary of calendar anomalies tests for FTSE100 and FTSE250 for sub samples 2007–2016.

Label	2007–2008	2009–2010	2011–2012	2013–2014	2015–2016
FTSE100 (returns)					
Monday		√			
January		√			
TOTM			√		
Halloween					
FTSE250 (returns)					
Calendar effects					
Monday			√		√
January					
TOTM			√		
Halloween					

Examining the data for the entire period, it may appear that both the FTSE100 and FTSE250 markets are not weak form efficient. However evaluating the results for sub samples reveals a more complete picture. Both markets are going through different states of efficiency across the periods. Sub sample periods of higher weak form efficiency are also different for the two indices: FTSE100 (2009–2010 and 2011–2012); FTSE250 (2007–2008). Non linear effects in residuals are also seen in all subsamples except the third subsample of the FTSE100(2011–2012). The FTSE100 showed the highest period of inefficiency in the first and fifth subsamples, while the subsample of highest inefficiency for the FTSE250 was the fourth subsample (2013–2014). Calendar effects are significant in different subsamples. In the subsample which closest approaches weak form efficiency of all the data studied (FTSE100, 2011–2012), a calendar anomaly is also significantly present (TOTM).

The financial crisis occurred in 2008–2009 and both the FTSE100 and FTSE250 underwent substantial downturns. In the period mostly preceding the financial crisis (2007–2008) the FTSE100 showed a high level of inefficiency (mostly international companies) while the FTSE250 (mostly domestic companies), showed a higher level of efficiency. Conversely in the period succeeding the financial crisis (2009–2010), the FTSE100 showed an opposite effect. In the period, mostly preceding the financial crisis (2007–2008), Calendar anomalies were not detected in the subsamples of both the FTSE100 and the FTSE250, but in the later period (2009–2010) they appeared in the FTSE100. In the period of the Brexit referendum (2016), which introduced a high level of uncertainty in the UK markets, both the FTSE100 and FTSE250 were relatively inefficient and calendar anomalies could be detected only in the FTSE250. In summary, both markets showed signs of improvements in efficiency and vice versa with calendar anomalies appearing and disappearing in a time varying fashion, and at times in coexistence with weak form efficiency. Such market behaviour supports the Adaptive Market Hypothesis, a conceptualisation of the dynamic nature of financial markets depending upon market conditions and participant actions.

5. Conclusion

In the current research, efficiency of two main stock indices, the FTSE100 and FTSE250 comprising the top 350 companies by market capitalisation on the London Exchange were tested over the period 2007–2016, a ten year period which included two significant events: the financial crisis of 2008–2009 and the Brexit Referendum of 2016. Given the characteristics of the distribution of stock returns, a mix of parametric and non-parametric tests were conducted. To test for the presence of the classic Random walk, a conceptualisation of weak form efficiency in the EMH: unit root, autocorrelation, variance constancy and tests for non linearity in residuals were conducted. Although one might have concluded that both markets were not weak form efficient over the whole period, analysis of the sub sample periods revealed a more complete picture. The evidence from these efficiency tests supports neither the idea of a market whose efficiency which improves nor is constant over time, but a dynamic market whose efficiency switches from efficient to inefficient and vice versa in support of the Adaptive Market Hypothesis.

From another perspective, Calendar anomalies such as the “the Monday effect,” “The January effect,” “The Turn-of-the-month-effect” and “The Halloween effect” were also tested with parametric and non-parametric tests: a GARCH(1,1) formulation and the Kruskal Wallis test and these too showed an inconstant, time varying behaviour. The movements from inefficiency to efficiency and vice versa was not concomitant for the two indices the FTSE100 and FTSE250, possibly given the nature of the underlying constituents. There was also support for the coexistence of market efficiency and calendar anomalies.

The results of this study support earlier research on the AMH in other markets (Lim and Brooks (2006), Todea et al. (2009), Ito and Sugiyama (2009), Hiremath and Kumari (2013) ,Urquhart and Hudson (2013), Urquhart and McGroarty (2014)), Boya(2017), Shahid and Sattar (2019).

In periods of uncertainty, an interesting behaviour has been found when analysing the two indices during the same sample period: dependence in the returns tends to be more pronounced during market crashes and times of political and economic uncertainty, evidence on which has been already reported in the papers by Charles, Darné, and Kim (2012) and Kim, Shamsuddin, and Lim (2011). Though strong evidence of any of the calendar effects is not evidenced, the time varying behaviour of the occurrence of Calendar anomalies and the fact that the sub-samples generate significant and insignificant statistics of different signs is once again, supportive of the Adaptive Market Hypothesis.

Overall, based on the evidence of this study, it can be concluded that financial markets in a developed country as the UK can undergo states of inefficiency moving to efficiency and vice versa in support of the Adaptive Market Hypothesis which gives a better understanding of market behaviour than the EMH on its own. The results of this study also suggest that the conceptualisation of an Adaptive Market can be very useful in the analysis of stock markets (that are often believed to be efficient).

5.1. Further research

The sample analysed in this research is of a total of ten years for the top 350 companies by market capitalisation, quoted on the London Stock Exchange. To get a more in-depth picture of the behaviour of stock returns, studies can be conducted over a longer period. Moreover, Calendar anomalies, which have not been found significant either in the FTSE100 or the FTSE250 may be present more prominently in indices covering smaller value stocks such as FTSE Small Cap Index or the FTSE Aim Index, which are subject to lower levels of daily scrutiny. The research could of course be extended also to other European and Asian stock markets. The manner in which AMH explains dynamic changes in the stock markets is preferred to the static description of efficiency proposed by the classical EMH. The conceptualisation of the Adaptive Market Hypothesis to explain the transformational nature of stock-markets, allows investors to study market conditions and devise elaborate arbitrage strategies that fit the current market environment. The adaptation of investors' strategies to the market is key for survival.

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Conflict of interest

All authors declare no conflicts of interest in this paper.

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