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| |  |  | | --- | --- | | |  | | --- | | Imię i nazwisko studenta: Marcin Wolszon | | | |  | | --- | | Nr albumu: 184554 | | | |  | | --- | | Poziom kształcenia: Studia pierwszego stopnia | | | |  | | --- | | Forma studiów: stacjonarne | | | |  | | --- | | Międzywydziałowy kierunek studiów: Inżynieria danych | | | |  | | --- | | prowadzony przez: Wydział Zarządzania i Ekonomii, Wydział Elektroniki, Telekomunikacji i Informatyki | | | Profil: Data exploration in management | |
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| |  | | --- | | **PRACA DYPLOMOWA INŻYNIERSKA** | |
| |  | | --- | | Tytuł pracy w języku polskim: OPRACOWANIE APLIKACJI DO WYKRYWANIA WYBRANYCH EFEKTÓW KALENDARZOWYCH DLA INWESTYCJI |  |  | | --- | | Tytuł pracy w języku angielskim: DEVELOPING AN APPLICATION FOR DETECTION OF SELECTED CALENDAR EFFECTS FOR INVESTMENTS |  |  | | --- | |  | |
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Gdansk, 2023

**ABSTRACT (IN polish)**

Głównym celem niniejszej pracy dyplomowej jest opracowanie aplikacji opartej na języku Python, zdolnej do wykrywania anomalii kalendarzowych, takich jak efekty miesiąca roku i dnia tygodnia, w zwrotach z akcji. Motywacją stojącą za takim pomysłem było dostarczenie narzędzia analitycznego, które mogłoby pomóc inwestorom w podejmowaniu świadomych decyzji, ponieważ, jak wynika z przeglądu literatury dokonanego podczas tych badań, wykonywanie obliczeń statystycznych i tworzenie zaawansowanych modeli, takich jak EGARCH, jest czasochłonne i wymaga co najmniej średniozaawansowanej wiedzy z zakresu statystyki.

Część badawcza niniejszego artykułu obejmuje analizę istniejącej literatury na temat anomalii kalendarzowych na różnych rynkach. Poprzez analizę tych badań i zastosowanie metodologii w nich stosowanych, niniejsza praca ma na celu wykorzystanie metod statystycznych w praktycznych rozwiązaniach algorytmicznych, które mogą być przydatne w analizie różnych strategii i decyzji inwestycyjnych. Aby przetestować opracowaną aplikację, zebrano dane z czterech różnych rynków, a przeprowadzona analiza zaowocowała właściwą analizą danych indeksów pod kątem anomalii kalendarzowych.

**Słowa kluczowe**: efekty kalendarzowe, efekt dnia tygodnia, efekt miesiąca roku, ekonomia behawioralna

**ABSTRACT**

This diploma thesis main goal is to develop a python-based application, capable of detecting calendar anomalies, such as month-of-the-year and day-of-the-week effects, in stock returns. Motivation behind such an idea was to provide analytical tool that could help investors in making well informed decisions, because, what comes in conclusions drawn from literature review done during this research, performing statistical calculations and creating advanced models like EGARCH is time consuming and requires at least intermediate knowledge in statistic field.

The research part of this paper involves analysis of existing literature about calendar anomalies on different markets. By analysing this studies, and applying methodologies used in them, this thesis aims to use statistical methods in practical algorithmic solutions, which can be useful in analysing different investment strategies and decisions. To test the developed application, data from four different markets were gathered, and performed analysis resulted in proper analysis of given indexes in terms of calendar anomalies.

**Keywords**: calendar effects, day-of-the-week effect, month-of-the-year effect, behavioural economy

**Breakdown of authors contributions**

**Miłosz Wójcik:**

2.2 Main market hypothesis as a background for calendar effects

2.2.1 Efficient Market Hypothesis

2.2.2 Adaptive Market Hypothesis

2.3 Calendar effects classification and characteristics – overview

2.3.1 Day-of-the-week

2.4 Literature review – overview and 11 first entries

3.1 Researched markets – statistics, figures

3.2 Data preparation – guidelines for application usage, pre-processing, tests conclusions and figures

3.3 Linear Regression Model

3.5 Detection of calendar effects

**Marcin Wolszon**:

2.1 Investment theory – definition and characteristics of investment

2.3 Calendar effects classification and characteristics – Alex Plastun findings

2.3.2 Month-of-the-year effect

2.3.3 Holiday effect

2.3.1 Turn-of-the-month effect

2.4 Literature review – 5 last table entries and conclusions

3.1 Researched markets – markets overview, conclusions

3.2 Data preparation – tests descriptions and formulas,

3.4 EGARCH modelling

4. Conclusions and further development

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INTRODUCTION

Since the efficient market hypothesis was brought to life, it became a cornerstone of modern financial theory, asserting that prices always represent all information that is available at any given time. This hypothesis implies that no investor has an advantage in predicting a return on a stock price because no one has access to information not already available to everyone else. Correctness of EMH has been subject of rigorous analysis, and a tremendous amount of effort was put to test this theory.

One of most compelling critiques of the EMH comes from the study of market anomalies - irregularities or deviations in market behaviour that seem to contradict the hypothesis. These anomalies represent patterns that appear to provide an opportunity for superior investment returns, challenging the notion that markets are always efficient.

In recent years testing for such anomalies became an active area of empirical and behavioural finance study. Academics and industry experts have conducted extensive research to explore these phenomena. There are many types of anomalies, the size effect, momentum anomalies, technical anomalies or calendar anomalies, which gathered particular attention due to their implication for market predictability.

Calendar anomalies refer to patterns in stock return that are associated with specific time of the year, week, or day. Such anomalies can be correlated with season of the year, beginning/end of the year, week, month and holiday, or to religious or political events. Persistent presence of these patterns across global markets and over extended periods has generated a great deal of research, making it a popular topic in financial literature.

Calendar anomalies have been tested in a large number of studies, and many of them found such effects on stocks on many markets, throughout the last 50 years. But many studies performed did not detect any of such patterns. From this, an ambivalent conclusion can be drawn, that there is possibility that some indexes may be affected by these anomalies, and some may not. By looking at the above outcome, it would seem responsible for an investor to be aware if a specific index that an investor looks forward to invest in, is affected or not by such anomalies, but doing proper scientific research is definitely too complicated and time-consuming to perform it for every potential investment. Investing without it is a very stressful and complicated job. Number of factors and forces that may influence the market and individual indexes far exceeds human capabilities. Without suitable tools or applications, it seems impossible to perform at least correct analysis.

The main goal of this paper is to develop such an application that would automate calendar effects analysis, that should test given stock for occurrence of calendar anomalies and provide another factor, one of many, to financial analysis, helping to make an investment decision. By performing data analytics and using leverage of algorithmic detection, this application seeks to provide a tool for investors and researchers to identify calendar anomalies in financial markets.

Additional goal of this study is to perform analysis on 4 chosen markets, NASDAQ, LSE, WIG and TSE, which will serve as a test for our application, but also will serve as proper research in detecting calendar anomalies on given indices. Research period covers the period of 10 years, with return data for chosen indexes with dates starting from 12.11.2013 and ending on 08.12.2023.

This paper consists of 3 chapters. First chapter provides theoretical foundations, briefly describing theory of investment, efficient and adaptive market hypotheses, and collective description of selected calendar effects, the patterns in stock market that seems to happen at certain time of the year or week, with information of some of the scientific work done in this field, including the methods used by researchers to study markets and detect these anomalies.

The second chapter describes data and methodology used in this study. It consists of a description of the markets from which data were gathered, but also informs how data was prepared and what tests were performed to make sure it's good for this study. The following part describes the models that were used to examine volatility of tested indexes. Two models were used for this purpose: linear regression model and EGARCH model. We explain how these models work and why they are appropriate to use in this type of financial analysis. The most important part of this chapter is the presentation of output of our application for every chosen index, which includes all calculated descriptive statistics, results of applied models and insights drawn from specific outcomes.

Third chapter consist of conclusions gathered throughout the entire research along with key improvements proposals for the developed application, in terms of additional functionalities, wider range of discovered calendar effects, user interface enhancement and overall efficiency.

2. THEORETICAL BACKGROUND

2.1 Investment theory – definition and characteristics of investment

Investing is one of basic economic activities in modern human life. In a market economy it is necessary condition for this market to develop. According to Jajuga and Jajuga (2006) investment is the sacrifice of current consumption for future uncertain benefits. This sentence outlines for us the three basic characteristics of investment. First, to invest any amount of resources, we have to split all what we have to part which we will spend on consumption and to part which we decide to ,,freeze” in investment, so in consequence we are losing access to our resources for given time

Because length of period in which investment is active is fundamental to its prospective return, time is an essential characteristic of every investment. How long one is holding shares, how fast someone is cashing revenue, is directly related to time of actions, both making and ending the investment. But time can be viewed differently, as the date factor determining the success of investment, every calendar effect that will be brought in this paper is an example of how the time of the month, year etc. can influence the investment. Time can be also defined as a global factor, time of war, time of prosperity, bull or bear market, such time factor is undeniably important.

Third and last characteristic of investment is risk, which distinguishes it from savings, which is devoid of such risks, with exceptions such as inflation or failure of bank deposit. Risk is the potential that the rate of return on an investment will not match the investor's expected rate of return. In this risk determination, there are two types of risk (Jajuga, 2006):

* positive risk occurs when the realized income rate exceeds the predicted income rate;
* negative risk occurs when the realized income rate falls short of the expected income rate.

Such a dual look on risk can be very reasonable and responsible, in some cases returns regularly being bigger than expected could be a sign of higher risk.

There are many factors that determine the risk of investment, the most basic ones are (Jajuga, 2006):

* type of financial instrument: there are 4 basic types of financial instruments, deposits and money market instruments, bonds, shares and derivatives;
* issuer of the financial instrument (state treasury and government agencies, state administration units, financial institutions, companies. The risk is related to failure to meet the conditions by, for example, the stock exchange.

Financial risk is a crucial concept; in today's world, it is hard to imagine analyzing an investment without considering its risk. One could think that for example bank deposit is a riskless financial tool, but when you count inflation it turns out that there is risk in it too. What's more, the chance of the collapse of the business entity in which the cash was deposited should be taken into account.

According to F.K. Reilly and K.C. Brown, an investment is the commitment of a specific sum of money for a predetermined length of time with the expectation of a return in the future. The investment bears risk and compensates the investor for the time invested, expected inflation rate, and time commitment. An investment with an anticipated future return that will raise the amount committed today by a known amount is made by the investor (Reilly, Brown 2001). This definition aligns very well with the one from Dziworska (1993), she defines investing as funds that an investor has purposefully distributed in order to increase his income. If resources and earnings are represented by money, then investment is a continuous commitment of cash in order to obtain cash later, however investing can be seen as a process of converting cash into other goods (Różański 2006)

Investing is a resource that cannot be consumed, and its purpose is to generate income, and as seen in all definitions, it's associated with risk, because the amount of money we are going to obtain is in most cases not known (Luenberger 2003). Obvious examples of investment are stocks and bonds, but it can also be a bank deposit or real estate. If we assume that investing`s purpose is to generate wealth through creating income or raising value, which can be then exchanged to income, then all above are meeting this condition (Krtizman 2011).

Another way to examine the investment is from the perspective of cash flow over a specific time frame. Therefore, the investment's objective can be to generate a cash flow stream that satisfies the investor's needs. Still, since there is often some degree of uncertainty associated with cash flows, creating or matching cash flows primarily focuses on controlling this uncertainty, for example by lowering the level of risk. More financial activities are covered by the expanded definition of investment presented here, which is defined as creating and matching a specific time distribution of cash flows, than by the standard definition (Luenberger 2003)

The most crucial thing for an investor to do is to accurately evaluate the return on investments and allocate funds to the projects that will benefit him the most—that is, projects that will maximize returns while carrying a manageable amount of risk. Because markets are dynamic, investments are dynamic as well; as a result, the value of investments fluctuates over time, affecting the optimal portfolio's composition. The above mentioned factors led investors to perform investment analysis, which is the process of assessing potential courses of action and identifying the most advantageous one (Jajuga, Kuziak, Markowski 1998; Luenberger 2003).

The purposes of investing are defined as spending cash resources for securing savings or to benefit later. It is then protection of owned resources, anticipating to profit from them or to receive income from them. These objectives can be summed up as delaying consumption till later or using capital to increase it. To basic purposes of investing counts:

* gathering resource for consumption purposes - the goal is achieved when value of investment is not smaller than predicted price of targeted good;
* preservation of liquidity: permits a quick cash conversion from the chosen financial instrument;
* growing the capital size in order to achieve the highest feasible capital value at the conclusion of the investment period;
* security: the goal of investing is to guard against capital loss;
* obtaining a stable income - by investing, one obtains funds at regular intervals to enable current consumption.

The type of investment researched in application is this basic one, so buying shares on stock exchanges.

2.2 Main market hypothesis as a background for calendar effects

2.2.1 Efficient Market Hypothesis

The majority of research investigations during the 1960s, beginning with Fama (1965) and Samuelson (1965), concluded that the capital markets were efficient. This is when the Efficient Market Hypothesis first emerged. Over the ensuing decades, an increasing number of research began to refute the hypothesis in all three of its formulations: weak, semi-strong, and strong. In Fama (1970) defined an efficient market as “a market with a great number of rational, profit-maximisers actively competing, with each trying to predict future market values of individual securities, and where current important information is almost freely available to all participants”.

Going back to Fama (1970), the weak form of the Efficient Market Hypothesis (EMH) was defined as the actual situation when all of the historical financial knowledge that has ever been is incorporated into the current pricing of financial assets. Thus, the hypothesis lends credence to the notion that investment in these financial assets cannot yield extraordinary rewards for investors. It is implied by this EMH form that prices will random walk. A substantial amount of research has been done on the random walk nature of stock prices. According to the random walk theory, it is impossible to forecast how prices will change in the future. An increase on one day does not necessarily indicate that there will be another increase or reduction on the next day.

The semi-strong form of the Efficient Market Hypothesis (EMH) postulates that the prices of financial assets always reflect all available information on the market, including past prices and other historical data (i.e., this form also includes the EMH's weak form). In addition, prices adjust quickly and impartially to consider any new information that is made available to the public and enters the market. If a capital market has a semi-strong form of EMH, neither technical nor fundamental research can tell how to allocate an investor's money such that the profit margin is better than it would be if the investor invested in a randomly selected portfolio of financial assets.

The strong form of the Efficient Market Hypothesis (EMH) postulates that prices consider all available information on a market, including all private information about a financial asset, all new public information (semi-strong form), and historical financial information (weak form).

Extensive research was conducted to evaluate each of the three categories of EMH. While opinions about the weak form of EMH (which includes random walk theory) were divided, the majority of them invalidated the strong and semi-strong forms of EMH, which are not supported by financial data. A small number of weak form studies supported the weak form of EMH by demonstrating that the aberrant returns are mostly due to chance and that the likelihood of an overreaction is roughly equal to the likelihood of an underreaction. Another typical conclusion is that the anomalies are caused by the methods employed since they tend to vanish when adjustments are made to the models that are used.

Prices, probabilities, and preferences - the "three P's of Total Investment Management" (Lo, 1999) - can be used to sum up the present EMH paradigm. The principle of supply and demand, one of the most fundamental and important concepts in contemporary economics, is where the three Ps got their start. According to this theory, the intersection of the supply and demand curves—which show the schedule of quantities producers are willing to supply at different prices and the demand curve, which shows the schedule of quantities consumers desire at different prices—determines the price of any commodity as well as the quantity traded. The point at which these two curves intersect is known as the "equilibrium," or the price-quantity combination that simultaneously meets the needs of producers and consumers.

While many tests have taken into account the features of probability implicit in asset values, the majority of the early tests concentrated on determining if the prices of certain financial assets did fully reflect different types of information (Cootner, 1964). However, the most persistent criticisms of the EMH centre on the choices and actions of market players. Assuming that investors optimise additive time-separable anticipated utility functions from specific parametric families—such as constant relative risk aversion—is the traditional method for modelling preferences. However, behavioural biases that are common to human decision-making under uncertainty have been documented by psychologists and experimental economists, including: overconfidence, overreaction, loss aversion, herding, psychological accounting, miscalibration of probabilities, hyperbolic discounting, and regret. These biases have negative consequences for an individual's economic welfare (Lo, 2004).

2.2.2 Adaptive Market Hypothesis

Adaptive Market Hypothesis (AMH) is a concept in financial engineering designed by Andrew W. Lo in 2004. It is an approach influenced mostly by “evolutionary psychology” which applies the principles of human behaviour such as competition, reproduction and natural selection to financial interactions. It is providing a dynamic perspective of financial market and investors strategies which implies that investors may behave non-rationally in unusual situations such as bubbles, crushes and crisis. According to Lo (2004) investors behaviour such as overconfidence and overreaction is consistent with evolution models which is also confirmed by behavioural economists.

The ability of investors to learn and adjust to the market's changing conditions is crucial for AMH to be the harmonisation of EMH. As a result, financial markets may occasionally be incorrect, but they have learned from their mistakes and have evolved to become correct until they make another one. According to AMH, cyclical recurrence of market inefficiency is an indication of adaptation. As the expansion to Lo hypothesis - Lim and Brooks (2011) presented two criteria to test this theory:

* The market efficiency should be varying through time;
* The market efficiency should be dependent on market conditions (i.e., financial crises, market crashes, stock bubbles).

Scholarly academics have given the AMH idea a great deal of attention since it first surfaced by conducting scientific research and providing strong evidence of that hypothesis for various markets across the world. Zhou and Lee (2013) performed an automatic portmanteau test and automatic variance ratio test to confirm that AMH applies to the Real Estate Investment Trust (REIT) market.

2.3 Calendar effects classification and characteristics

Financial markets are very much reliant on many factors such as its size, location and even given time frame. While market anomalies should be linked to investors’ behaviour and trading strategy there is still a field of studies based on discovering patterns in stock returns. Numerous calendar effects are discovered in studies, especially as it contradicts Efficient Market Hypothesis (EMH) developed in 1965 independently by Samuelson and Fama. The ability to identify correlations in such anomalies allows investors to improve their portfolio, increase return on investment and, to some extent, regulate the flow of money in the market. These effects may not influence stock returns directly but still can be used as guidelines for investment decisions. Performing wide analysis of this field leads to improvement of analytic tools used currently by economists and investors.

Plastun, Bouri, Gupta and Ji (2022) found calendar anomalies in various passion investment markets like diamonds, fine wines or stamps. Most common anomalies in these markets are day-of-the-week and month-of-the-year effects; they also find that some prices follow the Halloween Effect.

Calendar effects are widely researched for each particular stock market individually as there are multiple factors influencing its behaviour. Operation time differentiates markets as some of them may have other opening hours and days which leads to shift in investors strategies. While some attributes may differ, the conclusions are mostly the same, and anomalies such as Monday’s effect or January effect are discovered empirically for almost every index.

2.3.1 Day-of-the-week effect

Day-of-the-week effect is a group of anomalies mostly researched in studies worldwide. This can be described as a situation where the returns on certain days are negatively high compared to other days. Even in Fama (1965) studies he reports that variance on Monday is even about 20% greater than for other days. It is caused by the fact that Monday’s return is calculated over three calendar days as the weekend is counted in. First time Monday effect, or so-called “weekend effect”, was discovered and defined by Cross (1973) and French (1980). It was also found that the variance on Monday is more than three times of other week days – furthermore, 3.4% of Monday return differential due to delay in announcements after Friday market close. Weekend effects are further confirmed by multiple scientists for varied types of markets and time frames. The UK markets FT 30 and FTSE All-Shared Index were examined by Theobald and Price (1984) for years 1975-1981 and they confirmed negative market returns on Monday. Similar studies conducted by Gibbons and Hess (1981) provide the same result for 30 stocks of Dow Jones Industrial (DJI) index.

Lower returns on Monday have reflection on Friday as return on that day is statistically higher than for others. This has been proven in parallel in the previously listed papers of Cross (1973), French (1980), Theobald and Price (1984) and Gibbons and Hess (1981). Therefore a “weekend effect” is affecting not only Monday stock returns. Reasoning for that was presented by Nikunj and Martin (2015) as some traders close their short positions on days when the market is closed. They typically buy on Friday and reopen their position as short sellers on Monday, which results in bigger profits on Friday and reduced returns on Monday. The Friday returns subtracted by the subsequent Monday returns indicates the magnitude of the weekend effect.

Studying Singapore, Malaysia, Hong Kong, Thailand, and Taiwan from 1975 to 1988, Wong, Hui and Chan (1992) discovered a day-of-the-week effect in all but Taiwan. These four markets had high positive returns on Friday and negative mean returns on Monday or Tuesday, which was in line with findings from Rogalski (1984) in the US market from 1974 to 1984 and Condoyanni, O’Hanlon, Ward (1987) in the markets of Australia, Canada, France, Japan, Singapore, and the UK from 1969 to 1984. This is also in line with a recent study by Nageswari and Selvam (2011), who looked at returns on Tuesdays and Fridays in the Indian market from 2000 to 2010. Al-Khazali, Koumanakos and Pyun (2008) also noted the lower Tuesday and higher Friday returns in Greece from 1985 to 2004. In their 1985–1989 analysis of Canada, Athanassakos and Robinson (1994) discovered a strong, statistically significant negative Tuesday effect. Moreover, this effect has become more pronounced with time. For the lower capitalization portfolios, negative Tuesday returns have often outperformed negative Monday returns. According to Brooks and Persand (2001), there is a notable Wednesday effect in Taiwan and substantial negative returns on Tuesdays in Malaysia and Thailand. It is confirmed by Jaffe and Westerfield (1985a) and Dubois and Louvet (1996) that Tuesdays typically see negative daily returns in various Pacific countries.

First studies of day-of-the-week effects were conducted by, among others, Cross (1973), he conducted his observation without performing any statistical test but purely empirically. Further research by French (1980) or Smirlock and Starks (1986) examined indexes based on empirical analysis of stock return for specified time frames. Nonetheless, Rogalski (1984) notes that the Monday effect is negative but not statistically significant using linear regression   
model (OLS), F-tests, and t-tests. Other studies of Jaffe and Westerfield (1985a,1985b) and Chang, Pinegar, Ravichandran (1993) for non-US markets confirm that Monday returns are on average negative but also statistically significant. More recent day-of-the-week effect tests of Chukwuogor-Ndu (2006) finds evidence of such anomaly in seven out of fifteen European countries not only by comparison of daily stock returns but also conducting normality tests and homogeneity tests.

When analysing day-of-the-week impacts, ARCH/GARCH models are frequently used to control for variations in volatility as well as mean return variations. Using a GQARCH(1,2) model, Apergis and Eleptheriou (2001) examine the volatility of daily returns on the Athens Stock Exchange from 1990 to 1999 and conclude that persistence in volatility clustering suggests inefficiency. Using daily return and volume data for two emerging markets, Korea and Thailand, Kamath and Chusanachoti (2000) conclude that volume has no effect on the ARCH or GARCH process in a GARCH model. Adrangi, Raffiee, and Shank (1999) use a TARCH model with moving averages to account for asymmetric effects as they study volatility persistence in returns in the stock markets of Greece, Portugal, and Spain. Every market displays tenacity and volatility.

2.3.2 Month-of-the-year effect

Month of the year effect describes cluster of effects that are related to which time of year they occur. Berges, McConnel and Schlarbaum (1984), examined Canadian stock during 1951–1980 and found higher average returns in January, these results were consistent with work Haug and Hirschey (2006), who examined US market stock for years 1802-2004. The strength of this effect can be elevated by the fact that the imposition of capital gains tax in 1973, didn`t influence the January effect at all. Ciccone and Etebari (2008) analysed US market and it reconfirmed the January effect, but they also found quite significant anomaly in September

A possible "March effect" is suggested by a study looking at the Indian stock market. This "March effect" correlates with timing of the Union budget declaration (Elangovan, Irudayasamy, Parayitam, 2022), which suggests that certain policies and local events may have an impact on stock prices during specific months.

Jeffrey Jaffe and Randolph Westerfield found only weak evidence supporting monthly pattern in many countries, but they did find stronger evidence for a last day of the month effect, as well as evidence for country unique monthly patterns, often not consistent with other markets (Jaffe, Keim and Westerfield, 1989)

2.3.3 Holiday effect

Holiday effect, or pre-holiday effect refers to anomalies where stock returns are abnormally different in the period leading up to the holidays. Cadsby and Ratner (1992) found a pre-holiday effect in the markets of Japan, UK, Australia, Italy, Switzerland, West Germany and France. Ariel (1990) examined the US market for the period 1963-1982 and found a positive pre-holiday. In 2005 Chong and others found a negative pre-holiday effect in the USA, UK and Hong Kong during 1973–2003, which contradicted the Ariels findings from fifteen years earlier

Seyyed, Abraham and Al-Hajji (2005) performed analysis for the Saudi Arabian market in the years 1985–2000. They discovered an anomaly: a decrease in trading activity during Ramadan, which caused a drop in volatility. In the United Arab Emirates, Bahrain, Kuwait, Muscat, Qatar, Saudi Arabia, and Dubai, a more recent study found very similar fluctuations during Ramadan (Ariss, Rezvanian and Mehdian, 2011).

Al-Hajieh, Redhead and Rodgers (2011) examined market returns at the beginning and end of Ramadan period in years from 1992 to 2007, the study discovered a high degree of volatility in Bahrain, Egypt, Jordan, Kuwait, Qatar, Saudi Arabia, Turkey, and the United Arab Emirates.

Holidays have a strong influence on one’s mood, and many studies indicates that investors sentiment is related with holidays period (Bialkowski et al., 2012; Yang, 2016). In the end stock prices depend on investors actions, and it is proven that investor sentiment influences stock prices. (Baker & Wurgler, 2006; Neal & Wheatley, 1998).

2.3.1 Turn-of-the-month effect

The turn-of-the-month effect, or end-of-the-month effect in stock prices is another financial phenomenon where stock returns are anomalously higher around the end of the month compared to other days. In 2022 study was carried out to analyse United Kingdom stock market for years 1990 - 2021, and effect was detected both in stock indices and for the liquid stocks. (Vidal 2022). In this study, researchers also found evidence for greater cash flows in given periods. The Russian bond and stock market were examined for years 1998-2008, this period covered two bull markets, two bear markets and two recession processes, and strong support for turn-of-the-month effect was found. This study also included US bond and stock indexes, and here similar findings for end-of-the-month effect was found (Compton et al. 2013)

2.4 Literature review

One of the topics of discussion in the field of behavioral finance is the efficient market hypothesis. By forecasting stock prices, investors think they can beat the market. These forecasts can be derived from technical charts or patterns in time series, such as particular days of the week, months of the year, or days leading up to or following religious holidays. The body of research on calendar anomalies, such as day-of-the-week, month-of-the-year, and holiday effects on international stock markets, supports multiple hypotheses.

The findings of the literature review are shown in Table 2.1 with reference to the studies on calendar effects on various markets.

Table 2.1. Literature review – results.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| No. | Publication | Researched effects | Methodology | Insights |
| 1 | Gibbons, M. R., Hess, P. (1981) | Day-of-the-week | Return of index analysis | Equality hypothesis is rejected for each index in sample periods. Monday effect is common. Tuesday has slightly low return while Wednesday and Friday presents higher returns. |
| 2 | Rogalski, R. J. (1984) | Day-of-the-week;  Weekend;  Holiday;  Turn-of-the-year;  Combination of effects – weekend effect on January. | Equal means test | Monday effect is a non-trading weekend effect. Monday and non-trading weekend effects are highly related with January effect. Monday returns. Firm size highly influence appearance of calendar effect on the market. |
| 3 | Nageswari, P., Selvam. M. (2011) | Month-of-the-year | Kruskall-Wallis Test;  Regression model and ordinary least squares-method (OLS) | April has the highest mean return while October has most negative mean returns. There is significant correlation between returns on Tuesday and Friday. |
| 4 | Al-Khazali, O. M., Koumanakos, E. P., Pyun, C. S. (2008) | Day-of-the-week | Stochastic dominance (SD) analysis | Study documented a Thursday effect and a lower mean return on Friday in specific case Study however rejects hypothesis of abnormal returns on Monday |
| 5 | Brooks, C., Persand, G. (2001) | Day-of-the-week | Equal means test | Day-of-the-week effect was not identified in South Korea and Philippines. Other countries are insignificantly affected when average return was significantly positive or negative. |
| 6 | Chukwuogor-Ndu, C. (2006) | Day-of-the-week | Levene’s  test | In 7 countries there was present a Monday effect and in 7 others experiences negative return on Wednesday. There was high volatility of returns mostly experienced on Mondays. |
| 7 | Apergis, N., Eleptheriou, S. (2001) | Day-of-the-week | GARCH models | There were negative returns on Mondays and Tuesdays. |
| 8 | Haug, M., Hirschey, M. (2006) | January effect | Equal means test | For specifically created portfolios a January effect was visible negatively affecting stock momentum. It remains a small-cup phenomenon and was not affected by Tax Reform Act of 1986. |
| 9 | Ciccone, S. J., Etebari, A. (2008). | Month-of-the-year  Holiday | Equal means test  GARCH | January and September Effects are observed in United States. September effect is not affecting small firms. |
| 10 | Elangovan, R., Irudayasamy, F., Parayitam, S. (2022) | Month-of-the-year | ADF, PP, KPSS tests  ARIMA, GARCH | Returns showed high volatility on March which is caused with fact that in India budget is announced at the end of February. |
| 11 | Ariel, R. A. (1990). | Holiday | Equal means test | Holidays are significantly effecting mean return; pre-holidays return is much smaller then post-holiday |
| 12 | Al-Haijeh, Redhead, Rodgers (2011) | Time-of-the-year (Ramadan) | Wald-Wolfowitz test | Ramadan appears to have a generally positive impact on stock prices on markets in Islamic countries. |
| 13 | Vidal, Vidal-Garcia (2023) | Turn-of-the-month | GARCH models | End-of-the-month effect is present in United Kingdom stock indices. |
| 14 | Caporale, Zakirova (2017) | January, day-of-the-week and turn-of-the-month effects | OLS, GARCH, TGARCH, EGARCH | Study shows that once transaction costs are taken into account, anomalies disappear. |
| 15 | Compton, Kunkel, Kuhlemeyer (2013) | Month-of-the-year, day-of-the-week, turn-of-the-month effects | OLS | There is strong evidence of a persistent monthly pattern (no January effect), and strong evidence of weekday seasonality |
| 16 | Grotowski (2008) | Day-of-the-week, month-of-the-year, holiday, turn-of-the-month effects | GARCH | No evidence was found for the holiday effect and turn-of-the-month effect on the Polish market. Thursday and Friday effect occurs but only with statistical significance, not economical. The January effect is present for small and medium companies. |

*Source*: Author’s elaboration.

Studies mentioned in the above table discover calendar anomalies across different markets. The day-of-the-week effect, particularly the negative returns on Mondays, and the turn-of-the-month effects are frequently reported, however it is important to mention that many studies are not finding such patterns as well. The size of a firm on some markets seems to be correlated with significance of an effect. It was discovered that economic or cultural events, such as Ramadan in Islamic countries can influence stock prices. A wide range of methodologies is used to detect and analyse calendar effects, from traditional statistical tests like the equal mean test, to complex models like GARCH,EGARCH, or KPSS test.

3. DATA AND METHODOLOGY

3.1 Researched markets

To perform sufficient testing of our application with diverse data we decided to gather it from 4 markets NASDAQ, LSE, WSE, and TSE. Daily data of each major index of this markets were gathered for a period of ten years (2013.12.11 – 2023.12.08)

NASDAQ - National Association of Securities Dealers Automated Quotations Stock Market is a United States stock exchange, located in New York City. It is the second stock exchange in the world, after the New York Stock Exchange, in terms of market capitalization, being equal to $20.13 trillion. It was founded in 1971 by the National Association of Securities Dealers, now known as the Financial Industry Regulatory Authority. Calculation of the logarithmic returns over time for NASDAQ Composite Index (^IXIC) are visible on Figure 3.1.

Obraz zawierający Wykres, zrzut ekranu, linia, tekst

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Fig. 3.1. Logarithmic Returns Over Time for NASDAQ Composite Index (^IXIC).   
Source: Author’s elaboration.

Descriptive statistics along with normality tests were performed over NASDAQ Composite Index with observations displayed on Figure 3.2.

Obraz zawierający tekst, zrzut ekranu, Czcionka

Opis wygenerowany automatycznie

Fig. 3.2. Application output of generated insights from NASDAQ Composite Index (^IXIC) descriptive statistics.  
Source: Author’s elaboration.

Distribution of logarithmic return values is shown on Figure 3.3.

Obraz zawierający Wykres, diagram, zrzut ekranu, linia

Opis wygenerowany automatycznie

Fig. 3.3. Distribution and normal distribution of log returns for NASDAQ Composite Index (^IXIC).  
Source: Author’s elaboration.

LSE - London Stock Exchange is a United Kingdom’s stock exchange, based in the city of London. LSE has a very rich history reaching back to English coffeehouses in the 17th and 18th centuries, and the Royal Exchange founded and opened in 1571. According to data from World Federation of Exchanges, last updated on December 2 of 2023, market capitalization of London Stock Exchange Group is $3.29 trillion. FTSE 100 index of London Stock Exchange were selected for further research and calculation of the logarithmic returns over time for FTSE 100 (^IXIC) are visible on Figure 3.4.

Obraz zawierający tekst, Wykres, zrzut ekranu, linia

Opis wygenerowany automatycznie

Fig. 3.4. Logarithmic Returns Over Time for FTSE 100 (^FTSE100).  
Source: Author’s elaboration.

Descriptive statistics along with normality tests were performed over FTSE 100 index with observations displayed on Figure 3.5.

Obraz zawierający tekst, zrzut ekranu, Czcionka

Opis wygenerowany automatycznie

Fig. 3.5. Application output of generated insights from FTSE 100 (^FTSE100) descriptive statistics.  
Source: Author’s elaboration.

Distribution of logarithmic return values is shown on Figure 3.6.

Obraz zawierający Wykres, diagram, linia, zrzut ekranu

Opis wygenerowany automatycznie

Fig. 3.6. Distribution and normal distribution of log returns for FTSE 100 (^FTSE100).  
Source: Author’s elaboration.

WSE - Warsaw Stock Exchange is Polish stock exchange, founded in 1817 and currently located in the city centre of Warsaw. Market capitalization of WSE, according to their statistics is equal to EUR 252.8 billion, which, together with 416 companies quoted, makes it the biggest stock in central and eastern Europe. The most important indices of WSE are WIG 20 and WIG 30. Calculation of the logarithmic returns over time for WIG 30 index are visible on Figure 3.7.

Obraz zawierający Wykres, zrzut ekranu, tekst, diagram

Opis wygenerowany automatycznie

Fig. 3.7. Logarithmic Returns Over Time for WIG 30.   
Source: Author’s elaboration.

Descriptive statistics along with normality tests were performed over WIG 30 index with observations displayed on Figure 3.8.

Obraz zawierający tekst, zrzut ekranu, Czcionka

Opis wygenerowany automatycznie

Fig. 3.8. Application output of generated insights from WIG 30 descriptive statistics.   
Source: Author’s elaboration.

Distribution of logarithmic return values is shown on Figure 3.9.

Obraz zawierający Wykres, diagram, linia, zrzut ekranu

Opis wygenerowany automatycznie

Fig. 3.9. Distribution and normal distribution of log returns for WIG 30.  
Source: Author’s elaboration.

TSE - Tokyo Stock Exchange, is a Japanese stock exchange located in Tokyo, owned by Japanese Exchange Group (JPX). It was established in 1878, and was closed during the second world war. It was reopened in 1949. During the 1983-1990 period, TSE accounted for more than 60% of the world's stock market capitalization. In 2023, TSE market cap is equal to $5.65 trillion. Analysed index, Nikkei 225, is also the biggest index on Tokyo Stock Exchange. Calculation of the logarithmic returns over time for Nikkei 225 index are visible on Figure 3.10.

Obraz zawierający Wykres, tekst, linia, zrzut ekranu

Opis wygenerowany automatycznie

Fig. 3.10. Logarithmic Returns Over Time for Nikkei 225 (N225).   
Source: Author’s elaboration.

Descriptive statistics along with normality tests were performed over Nikkei 225 index with observations displayed on Figure 3.11.

Obraz zawierający tekst, zrzut ekranu, Czcionka

Opis wygenerowany automatycznie

Fig. 3.11. Application output of generated insights from Nikkei 225 (N225) descriptive statistics.   
Source: Author’s elaboration.

Distribution of logarithmic return values is shown on Figure 3.12.

Obraz zawierający Wykres, diagram, linia, tekst

Opis wygenerowany automatycznie

Fig. 3.12. Distribution and normal distribution of log returns for Nikkei 225 (N225).  
Source: Author’s elaboration.

Insights from descriptive statistics are repeatable across all stock exchanges indices that were researched. Each dataset demonstrated returns that significantly deviate from a normal distribution, as evidenced by a very low p-values from the Shapiro-Wilk tests. Standard deviations of returns indicate moderate volatility across all indices, while level of volatility varies, none of the datasets show excessively high volatility. All datasets exhibited fat tails with high kurtosis values, indicating a higher likelihood of extreme returns, both positive and negative. For all indexes except WIG, skewness had a negative value indicating a left tail, which means that there are more frequent small gains and a few significant losses. Lack of normal distribution can be caused by many factors, leverage effects, volatility clustering, fat tails observed in all four datasets, meaning more extreme movements, structural breaks and many others. It is hard to determine the cause but the effect is clearly visible on the chart.

3.2 Data preparation

For a correct usage of application the data have to be formatted with specific guidelines to avoid errors. The input file have to be in comma-separated values format and include a column indicating date and closing index value for that day. “Date” column has to be in date-time format so the program reads it correctly, however the order is not affecting application. “Close” column requires correct label with no spaces, starting with a capital letter. It is also important that “Close” column values should not have any null values and each float type observation needs to have a dot as a decimal separator. Sample dataset structure that suits input file requirements of the application and is often provided by market data sources is shown on Figure 3.13 for NASDAQ Composite Index.



Fig. 3.13. NASDAQ Composite Index dataset.   
Source: https://www.nasdaq.com/market-activity/index/comp/historical#google\_vignette

Upon the upload of the input file containing “Date” and “Close” columns, the application employs a pre-processing mechanism to meticulously remove outliers for smallest and biggest 1% of returns as well as all discovered null values. This critical step ensures the integrity of the subsequent analyses, mitigating the impact of anomalous data points on the reliability of the results. Furthermore, the application incorporates a logarithmic transformation of the Return column derived from the Close column of the input file. This transformation not only aligns with established financial modelling practices but also enhances the interpretability of the data, offering a more insightful perspective for econometric modelling. The seamless integration of these preprocessing steps into the application underscores its commitment to producing high-quality and accurate results in the realm of statistical and econometric analysis for market indices. Stage of pre-processing of the input file is fitted into “createReturnTable” function that is visible on Figure 3.14.

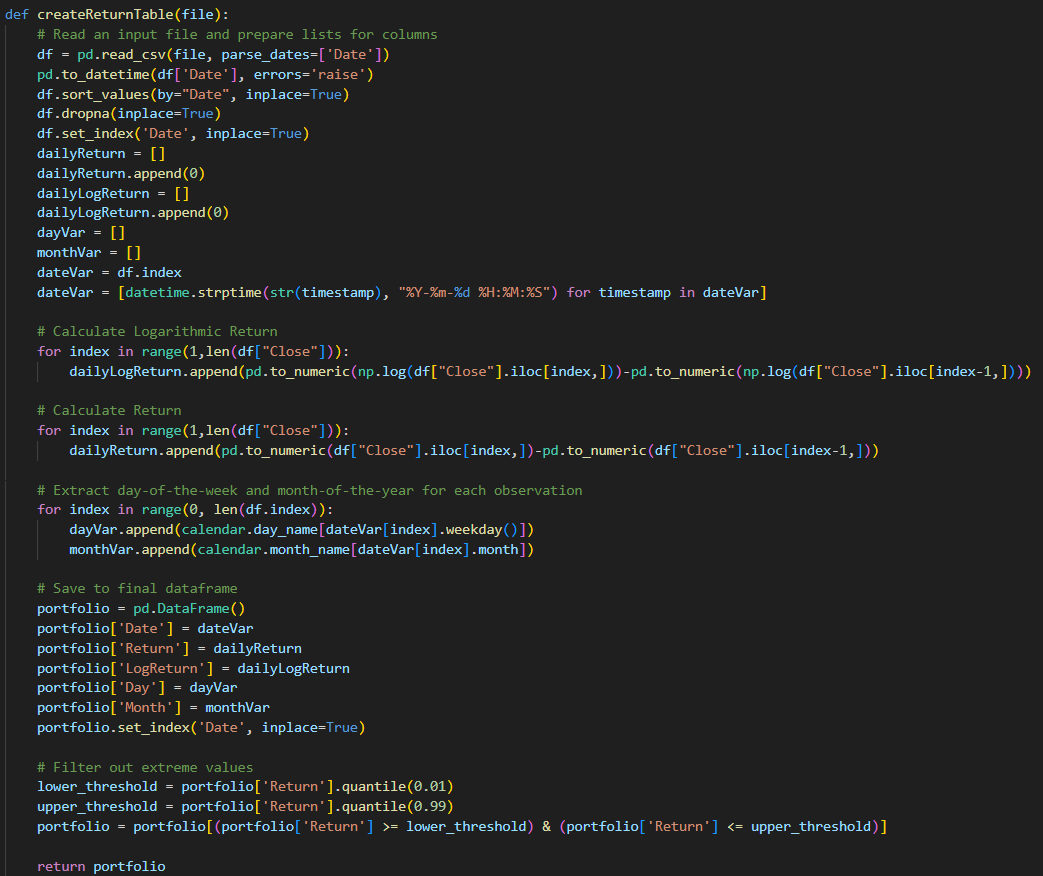


Fig. 3.14. “createReturnTable” data preprocessing function.   
Source: Author’s elaboration.

As the data stationarity is a crucial concept in time series analysis, three stationarity tests were performed to check if mean, variance and autocorrelation structure remain constant over time. To perform following test a Python “unitroot” library was used, chunk of code responsible for stationarity testing is visible on Figure 3.15 and sample application output for NASDAQ Composite Index is shown on Figure 3.16.

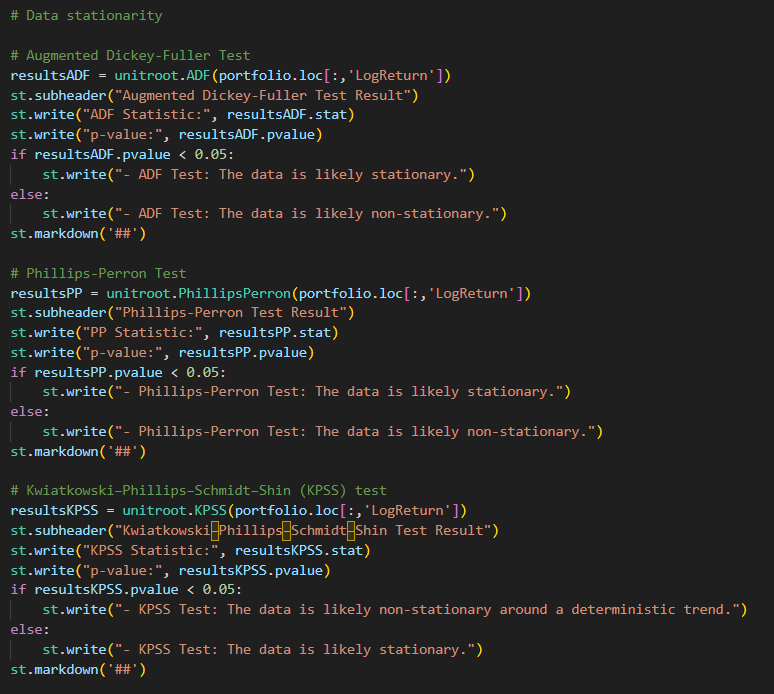


Fig. 3.15. Stationarity tests in python.   
Source: Author’s elaboration.

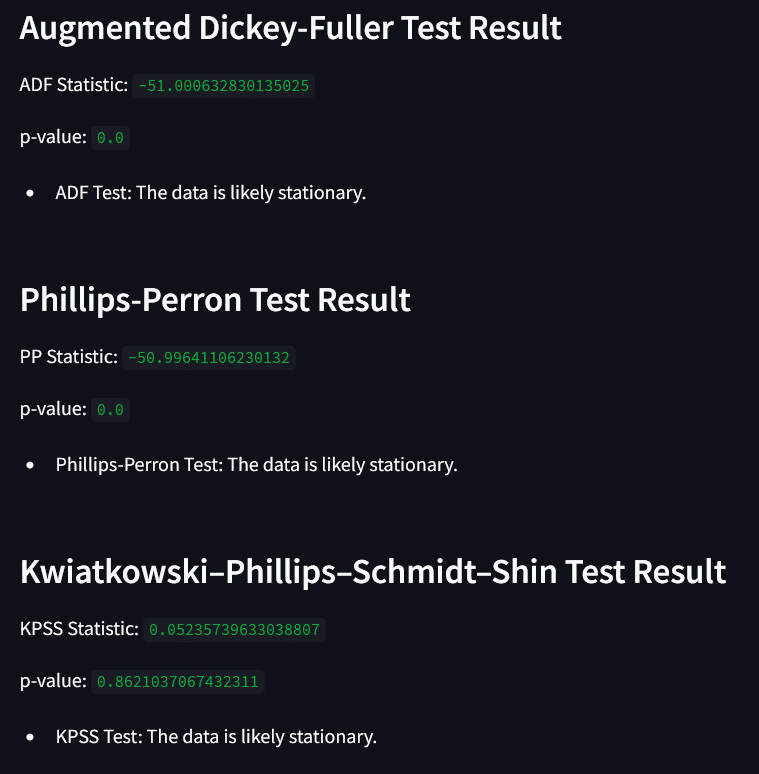


Fig. 3.16. Stationarity tests application output.   
Source: Author’s elaboration.

Augmented Dickey-Fuller test or ADF test is part of a category of tests called Unit Root Test, which is a method for testing the stationarity of time series. As the name suggests, ADF expand the standard Dickey-Fuller test to include a high order regressive process in the model. In time series analysis, ADF is frequently used, particularly when autoregressive models are involved. ADF test can be also represented as in Formula 3.1 (Source: https://www.machinelearningplus.com/time-series/augmented-dickey-fuller-test/).

(3.1)

where:

- the value of the time series at time ,

- the constant term (intercept) in the regression,

– a time trend, which may be included to account for deterministic trends in the data,

- the coefficient on the lagged value of the time series, indicating the speed of adjustment towards equilibrium,

- The lagged value of the time series, which is the value at time (),

- The change in the time series at times (), (),   
() respectively,

- the coefficients of the lagged first differences of the series,

- the error term at time ( t ), representing random noise not explained by the model.

A computed test statistic and p-values are the results of the test, which involves hypothesis testing with a null and alternate hypothesis.

Phillips-Perron (PP) Test is an nonparametric method of controlling for serial correlation when testing for a unit root. This method estimates the standard Dickey-Fuller test equation, and by modifying the alpha coefficient to account for serial correlation. This test is particularly useful because it doesn't require specifying a model for the autocorrelation structure of the time series. PP test can be described as in Formula 3.2 (Source: https://www.eviews.com/help/helpintro.html  
#page/content%2Fadvtimeser-Unit\_Root\_Testing.html%23ww184965).

(3.2)

where:

- estimate,

– the t-ratio of ,

– coefficient standard error,

– standard error of the test regression,

– consistent estimate of the error variance (),

– estimator of the residual spectrum at frequency zero.

Kwiatkowski-Phillips-Schmidt-Shin test - Third test that we perform to determine if the examined time series is stationary. This test is used to check this around a deterministic trend. It is somewhat similar to the ADF test, but it's important to remember that it does not mean that those tests can be used interchangeably. What differs KPPS test from other unit root tests, is the fact that presence of unit root is not the null hypothesis but the alternative, what is more, the absence of a unit root is not a proof of stationarity, but of trend-stationarity.

Results of each stationarity test for all researched indexes are shown in Table 3.1.

Table 3.1. Stationarity tests results.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Index | ADF test | | PP test | | KPSS test | |
| p-value | statistic | p-value | statistic | p-value | statistic |
| NASDAQ Composite (^IXIC) | 0 | -51 | 0 | -51 | 0.86 | 0.05 |
| FTSE 100 (^FTSE100) | 0 | -16.73 | 0 | -51.73 | 0.49 | 0.12 |
| WIG 30 | 0 | -36.71 | 0 | -48.34 | 0.89 | 0.04 |
| Nikke 225 (N225) | 0 | -49.32 | 0 | -49.35 | 0.83 | 0.06 |

*Source*: Author’s elaboration.

As you be seen each index proved to have stationary data independently from performed test, it indicates that its structure remains constant over time and there are no trends affecting return over time.

3.3 Linear Regression Model

Linear regression is used for modelling the relationship between a dependent variable and one or more independent variables, it assumes the linear relationship between these variables. There are many methods for creating such models. One of the most popular is Ordinary Least Squares (OLS). It aims to find the best-fitting linear relationship between dependent and independent variables, by minimizing the sum of residuals, which are squares of the differences between predicted values and observed ones. We use OLS in our application with usage of statsmodel library as per Figure 3.17 for both days of the week and months of the year. To the equation dummy variables were added, and they represent days or months, depending on which effect we are examining.

Obraz zawierający tekst, zrzut ekranu, Czcionka

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Fig. 3.17. OLS modelling for each day-of-the-week and month-of-the-year dummy variables.   
Source: Author’s elaboration.

To test for week days effects, such model is represented in formula 3.4 (Source: Gibbons and Hess 1981).

(3.4)

where:

- return of index in period ,

– disturbance,

– dummy variable for each day of the week that takes the value 0 or 1 depending on whether observation t occurs on a given day,

– coefficients associated with the corresponding day

OLS regression results for each researched index with day variable are shown in Table 3.2, while application example output of this statistic modelling for NASDAQ Composite Index is presented on Figure 3.18. Results that are statistically significant for significance level α = 0.05 are highlighted in bold.

Table 3.2. OLS regression results for each day of the week.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Day-of-the-week | NASDAQ Composite (^IXIC) | | FTSE 100 (^FTSE100) | | WIG 30 | | Nikke 225 (N225) | |
| Coef | p-value | Coef | p-value | Coef | p-value | Coef | p-value |
| Monday | 8.5955 | 0.083 | 0.4787 | 0.848 | **3.6085** | **0.002** | 11.8833 | 0.300 |
| Tuesday | 5.1901 | 0.276 | 3.7489 | 0.122 | 1.8131 | 0.115 | 21.1520 | 0.055 |
| Wednesday | 3.9646 | 0.404 | **5.7454** | **0.018** | -1.3212 | 0.251 | 1.7664 | 0.872 |
| Thursday | 6.3528 | 0.186 | **-6.3810** | **0.009** | -0.3930 | 0.735 | -1.1546 | 0.917 |
| Friday | 0.9274 | 0.847 | 1.3723 | 0.576 | -2.2184 | 0.057 | 3.2594 | 0.767 |

*Source*: Author’s elaboration.

Obraz zawierający tekst, zrzut ekranu, Czcionka, numer

Opis wygenerowany automatycznie

Fig. 3.18. OLS regression result for days of the week application output.   
Source: Author’s elaboration.

Similarly, OLS regression model can be used for test for month-of-the-year effects, the formula remains the same but each month has to be implemented by analogy to days. Results of such modelling are given in Table 3.3 with highlighted statistically significant means with the same level of significance as for Table 3.2. Sample application output for OLS regression for each month of the year is displayed on Figure 3.19 for NASDAQ Composite Index.

Table 3.3. OLS regression results for each month of the year.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Month-of-the-year | NASDAQ Composite (^IXIC) | | FTSE 100 (^FTSE100) | | WIG 30 | | Nikke 225 (N225) | |
| Coef | p-value | Coef | p-value | Coef | p-value | Coef | p-value |
| January | 2.6031 | 0.729 | 0.4179 | 0.911 | 0.7328 | 0.689 | -8.8983 | 0.618 |
| February | 3.9489 | 0.614 | 0.8288 | 0.835 | 0.6764 | 0.717 | 9.8967 | 0.581 |
| March | -5.6349 | 0.452 | 4.0406 | 0.287 | 0.2233 | 0.902 | -5.7316 | 0.736 |
| April | 2.5551 | 0.734 | 7.0823 | 0.067 | 2.0699 | 0.266 | 14.3469 | 0.401 |
| May | 8.0437 | 0.280 | -2.0243 | 0.596 | -1.9659 | 0.279 | 29.1902 | 0.097 |
| June | **15.3805** | **0.038** | -3.7431 | 0.330 | -0.1119 | 0.950 | 16.1239 | 0.336 |
| July | **15.4799** | **0.036** | 4.8671 | 0.191 | 1.4974 | 0.392 | 7.1474 | 0.670 |
| August | 6.5355 | 0.365 | -6.0365 | 0.109 | 0.3235 | 0.855 | -1.0200 | 0.951 |
| September | -7.1863 | 0.339 | -0.9107 | 0.809 | -2.0685 | 0.244 | -1.1832 | 0.946 |
| October | 8.7985 | 0.225 | -2.1920 | 0.558 | 1.6180 | 0.355 | 9.9083 | 0.560 |
| November | 11.7661 | 0.117 | 4.2067 | 0.265 | -0.3796 | 0.833 | 28.5780 | 0.105 |
| December | -3.6417 | 0.621 | 5.4655 | 0.144 | 0.9385 | 0.609 | -9.1180 | 0.589 |

*Source*: Author’s elaboration.

Obraz zawierający tekst, zrzut ekranu, menu, Czcionka

Opis wygenerowany automatycznie

Fig. 3.19. OLS regression result for months of the year application output.   
Source: Author’s elaboration.

3.4 EGARCH modelling

Financial markets are characterized by dynamic and time-varying volatility, a phenomenon crucial to understanding investment behaviour and risk management. To capture the intricate nature of volatility in analysis of calendar effects, Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model were introduced. EGARCH is a well-established method in financial econometrics known for its ability to model volatility clustering, leverage effects, and asymmetric responses to shocks.

Formula 3.5 represent expressed formula of the EGARCH model (Source: https://support.numxl.com/hc/en-us/articles/214502046-Exponential-General-Autoregressive-Conditional-Heteroskedastic-EGARCH-Model).

(3.5)

where:

– conditional variance at time t,

- intercept,

– model parameters,

– return at time t – 1

– conditional standard deviation at time t – 1

EGARCH model is a type of GARCH model that addresses the phenomenon of volatility clustering or conditional heteroscedasticity, within a time series of financial data. Volatility clustering is characterized by periods of high volatility followed by periods of low volatility, without significant autocorrelation in the data itself. The EGARCH model differs from the standard GARCH, which models the variance directly, where EGARCH uses logarithm of the variance. This approach allows better handling of situations in which positive and negative impacts of equal magnitude have different effects of volatility, which is seen often in financial data. To perform this econometric model arch library was used, its outcome were then visualized as per code visible on Figure 3.20.

Obraz zawierający tekst, zrzut ekranu

Opis wygenerowany automatycznie

Fig. 3.20. EGARCH modelling and output visualization.  
Source: Author’s elaboration.

The volatility calculated with EGARCH modelling is a crucial data derived from it. To represent its values over time subsequential plotting was made for each researched index. Calculations of mean volatilities Volatility for NASDAQ Composite Index is shown on figure 3.21.

Obraz zawierający tekst, Wykres, linia, zrzut ekranu

Opis wygenerowany automatycznie

Fig. 3.21. Volatility over time for NASDAQ Composite Index (^IXIC).  
Source: Author’s elaboration.

Volatility for FTSE 100 index is shown on figure 3.22.

Obraz zawierający Wykres, linia, tekst, zrzut ekranu

Opis wygenerowany automatycznie

Fig. 3.22. Volatility over time for FTSE 100 index (^FTSE100).  
Source: Author’s elaboration.

Volatility for WIG 30 index is shown on figure 3.23.

Obraz zawierający tekst, Wykres, linia, Czcionka

Opis wygenerowany automatycznie

Fig. 3.23. Volatility over time for WIG 30 index.  
Source: Author’s elaboration.

Volatility for Nikkei 225 index is shown on figure 3.24.

Obraz zawierający tekst, Wykres, linia, Czcionka

Opis wygenerowany automatycznie

Fig. 3.24. Volatility over time for Nikkei 225 (N225).  
Source: Author’s elaboration.

As can be seen in the figures above, each of the researched markets has, to some extent, demonstrated regularity in changes of volatility. However, vast majority of these observations is limited to a short period of time of about two years, not always consecutive, for instance years 2016 and 2018 for FTSE 100 index. With this said volatility clustering does not provide any hard evidence of calendar effects presence. Another approach of volatility analysis for detection of such anomalies is to observe its values for each examined period of time, in this thesis mentioned examination is performed in chapter 3.5. Moreover, volatility study in longer time frame is used mainly as an advisory tool to OLS modelling results due to values similarity for large samples.

3.5 Detection of calendar effect

Application provides insights of analysis in real-time in form of one sentence statements regarding discovered disparities in results of OLS regression modelling and GARCH modelling. The statistic significance of the result was also take into account while making conclusions of previous analysis.

For NASDAQ Composite Index (^IXIC) there were no day-of-the-week effects discovered while it is important to mention that the average Monday return was significantly higher than for other days as per Table 3.2. and Figure 3.25. Such observation is a useful information but is not statistically significant and the time frame of the analysis was wide while such anomaly could be notable in a shorter range of time. Analysis of a month-of-the-year effect for the same index resulted in June and July having much higher mean return and being statistically significant as per Table 3.3. and Figure 3.26. The volatility analysis indicates that at that time the market conditions were mostly stable comparing to other months as visible on Figure 3.27.

Obraz zawierający tekst, zrzut ekranu, diagram, numer

Opis wygenerowany automatycznie

Fig. 3.25. Average daily returns for NASDAQ Composite Index (^IXIC).  
Source: Author’s elaboration.

Obraz zawierający tekst, diagram, zrzut ekranu, numer

Opis wygenerowany automatycznie

Fig. 3.26. Average monthly returns for NASDAQ Composite Index (^IXIC).  
Source: Author’s elaboration.

Obraz zawierający tekst, zrzut ekranu, Czcionka, numer

Opis wygenerowany automatycznie

Fig. 3.27. Average monthly volatility for NASDAQ Composite Index (^IXIC).  
Source: Author’s elaboration.

FTSE 100 index (^FTSE100) had an extremely high average return on Wednesday and utterly low mean return on Thursday which may indicate a similarity in calendar effect to that found by Brooks and Persand (2001) for Asian markets. Both of this observations are in Table 3.2. and on Figure 3.28. Month-of-the-year analysis of the same index did not provided any statistically significant results, however overall high mean return in December and close to zero mean return in January might indicate January effect for this index as per Table 3.3. and Figure 3.29. Same results might also align with research of Nageswari, P. and Selvam. M. (2011) in which it was found that the April has the highest mean return, while October has overall negative mean return. In this case the equivalent of October is visibly an August.

Obraz zawierający tekst, diagram, zrzut ekranu, kwadrat

Opis wygenerowany automatycznie

Fig. 3.28. Average daily returns for FTSE 100 index (^FTSE100).  
Source: Author’s elaboration.

Obraz zawierający tekst, numer, diagram, linia

Opis wygenerowany automatycznie

Fig. 3.29. Average monthly returns for FTSE 100 index (^FTSE100).  
Source: Author’s elaboration.

Analysis of Polish WIG 30 index resulted in a significant weekend effect as the mean return on Monday is notably positive, while Friday mean return is markedly negative but not statistically important according to OLS modelling. These findings are visible in Table 3.2. and Figure 3.30. With this in mind it can be confidently said that Monday effect is a primary anomaly for WIG 30. There were no statistically significant month-of-the-year effects detected and volatility analysis did not resulted in any further insights regarding market behaviour.

Obraz zawierający tekst, zrzut ekranu, diagram, linia

Opis wygenerowany automatycznie

Fig. 3.30. Average daily returns for WIG 30 index.  
Source: Author’s elaboration.

Application evaluation of Nikkei 225 (N225) did not resulted in any calendar effects discovered but Tuesday mean return is visibly higher than for other days of the week, which can be seen in Table 3.2. and Figure 3.31. Average monthly returns for May and November are also significantly higher then for other months as per Table 3.3 and Figure 3.32. It is important to point out that the monthly mean volatility (Figure 3.33) is more scattered for particular months, which can indicate that this stock index is highly exposed to external factors that are not period. This, as a result, does not allow for the identification of long-term calendar effects.

Obraz zawierający tekst, zrzut ekranu, diagram, Wykres

Opis wygenerowany automatycznie

Fig. 3.31. Average daily returns for Nikkei 225 (N225).  
Source: Author’s elaboration.

Obraz zawierający tekst, diagram, numer, linia

Opis wygenerowany automatycznie

Fig. 3.32. Average monthly returns for Nikkei 225 (N225).  
Source: Author’s elaboration.

Obraz zawierający tekst, zrzut ekranu, Czcionka, Równolegle

Opis wygenerowany automatycznie

Fig. 3.33. Average monthly volatility for Nikkei 225 (N225).  
Source: Author’s elaboration.

4. CONCLUSIONS AND FURTHER DEVELOPMENT

Main goal of this study was to develop an application intended to perform multiple tests and calculations on given input data, to detect whether it is influenced by calendar anomalies. The purpose was to create a tool able to provide additional information for potential investors to help them in making an investment decision, which should be well thought out and based on good quality data. The application achieved its foundational goals, but it is ready for future enhancements and improvements, but it will be addressed in separate part. The development of application was preceded by detailed research through scientific literature regarding calendar effects, with results of this research included in the second chapter, where basic concepts like investing and efficient and adaptive market hypothesis are explained, but most importantly broad analysis of calendar effects, focusing on specific patterns, where and when they occur, and crucially what methods were used by researchers through years. On this information the whole structure of the application was based. Chosen methods are described in detail in the third chapter, along with description of our data sources, and procedures of data preparation. What is worth emphasizing, conclusion coming from the literature review and the resulting analysis of methods known nowadays, shows that detection of calendar anomalies can be done only on empirical studies. Effects of detecting calendar anomalies by developed application are shown in the last part of this chapter.

Path to realizing the goal of this research, which ended with delivery of a working application, provided additional positive value, with the theoretical section being the review of part of literature regarding calendar anomalies, providing insights and some kind of picture of the state of calendar anomalies on multiple markets. Mentioned earlier chapter third, includes outputs and results of analysis performed by application on four chosen indexes, which is in fact direct examination of calendar effects on given data.

Based on the used statistical operations, such as OLS and EGARCH modelling following observations can be made for calendar effects detection:

* Many observations of mean return can seemingly indicate particular calendar anomalies, but in fact these are not statistically significant so no clear statement can be made;
* Following the previous point, selected significance level is a crucial variable in detection of calendar effects;
* Volatility comparison should be performed over shorter periods of time to provide more unambiguous results;
* Independent variables in statistical modelling allow for a more realistic reflection of the operation of stock indices, which positively affects the output in terms of validity.

For further development of application, a number of propositions have been identified. Part of them refers to the statistical part of the whole project, proposing addition of other models from the GARCH family, or Kruskall-Wallis test, a non-parametric method for testing whether samples are originated from the same distribution. Analysing correlations between months and days may bring interesting conclusions. Natural path for this application should be widening the search range of specific calendar effects, Turn-of-the-month, turn-of-the-year, holiday effect, and more cultural events like Independence Day in July in the United States.

Other part of potential improvements touch user experience and data pre-processing part of the application. Much more intuitive and self-explanatory user interface could be planned and developed, enabling smoother and faster usage. Additional checks for correctness of input data are crucial for reliability of whole applications. Modifying the input section enabling it to accept more types and formats of data would definitely improve the whole project. All mentioned proposals have the potential of making the tool much more accessible and easier to use, increasing the number of potential investors being able to use such a tool.

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Code and used data is available on following GitHub: https://github.com/Marcian225/Calendar-Anomalies-Thesis