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CALENDAR ANOMALIES IN THE PORTUGUESE STOCK MARKET: A VERY LONG-TERM PERSPECTIVE (1900-2020)

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Abstract

An extensive amount of empirical work has been devoted to the examination of anomalies in the stock markets. However, very few studies analyse long periods and document how calendar anomalies behave. A long time series provides the possibility to analyse if calendar anomalies persist over time, or if they are sample specific. Moreover, a larger sample is essential to avoid problems with data mining, noise and selection bias (Lakonishok and Smidt, 1988).

Therefore, the present dissertation examines the existence of several calendar effects in the Portuguese stock market using approximately 116 years of data from an underexplored database. This is the most complete study in terms of the length of the period under analysis, being the first long term study in the Portuguese market.

The results show that the existence of calendar anomalies strongly depend on the "*eye of the beholder*" (Zhang and Jacobsen, 2013). Applying the standard OLS methodology, we document a significant effect in January, September, April and in Halloween. Contrarily, the worst significant months to invest in the stock market are in June and July. Nevertheless, when analysing the evolution of calendar anomalies over time, we detect some inconsistencies between methodologies applied. For instance, following the dynamic analysis of the annual t-statistics, the calendar effects do not exist in the market or are significantly weakening and vanishing. Furthermore, according with the *"Superior Predictive Ability"* test (Hansen, 2005), the well-known Halloween and January strategies cannot surpass the buy-and-hold strategy which supports the efficient market hypothesis.

The instability regarding the presence, behaviour and significance of the observed seasonal patterns casts doubt on investors' ability to exploit these calendar patterns and complicates the obtainment of conclusive implications regarding the market efficiency.

Keywords: Efficient Market Hypothesis; Long time series data; Seasonal anomalies; GARCH; Rolling Windows; Week-of-the-year effect; Superior Predictive Ability test
JEL-Codes: G10, G14

Resumo

Uma extensa quantidade de trabalho empírico tem vindo a ser dedicado no estudo de anomalias sazonais no mercado acionista. No entanto, poucos estudos analisam longos períodos e documentam como as anomalias do calendário se comportam. Uma série de dados longa oferece a possibilidade de analisar como as anomalias sazonais persistem ao longo do tempo, ou se dependem de uma amostra específica. Além do mais, é essencial para evitar problemas com data mining, ruído e enviesamento de sobrevivência (Lakonishok e Smidt, 1988).

Assim sendo, a presente dissertação analisa a existência de diversas anomalias de calendário no mercado acionista Português, utilizando cerca de 116 anos de dados proveniente de uma base de dados pouco explorado. Este é o estudo mais completo em termos de duração do período em análise, sendo o primeiro estudo de longa duração no mercado Português.

Os resultados mostram que a existência de anomalias do calendário depende bastante do "olho de quem vê" (Zhang e Jacobsen, 2013). Aplicando a metodologia padrão OLS, documentamos um efeito significativo em Janeiro, Abril, Setembro e no Halloween. Contrariamente, os piores meses significativos para investir na bolsa são em Junho e Julho. No entanto, ao analisar a evolução das anomalias de calendário ao longo do tempo, detectamos algumas inconsistências entre as metodologias aplicadas. Por exemplo, seguindo a análise dinâmica dos testes-t anuais, os efeitos de calendário não existem no mercado ou estão significativamente enfraquecendo e desaparecendo. Além disso, de acordo com o teste de "Capacidade Preditiva Superior" (Hansen, 2005), as conhecidas estratégias de Halloween e no mês de Janeiro não conseguem superar a estratégia de comprar e manter, o que suporta a hipótese de mercado eficiente.

A instabilidade em relação à presença, comportamento e significância dos padrões sazonais coloca em dúvida a capacidade dos investidores de explorar esses padrões de calendário e complica a obtenção de implicações conclusivas em relação à eficiência do mercado.

Palavras-chave: Hipótese do Mercado Eficiente; Séries de dados longa; Anomalias de calendário; GARCH; Rolling Windows; Efeito semana do ano; Teste de capacidade preditiva superior

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1. Introduction

Since a few decades ago, there has been a significant amount of literature effort to study the existence of irregularities in stock markets. Calendar anomalies are basically defined by the tendency for the stock returns to exhibit a systematic pattern in a specific calendar period (Borges, 2009; Lobão and Lobo, 2018). Evidence of these anomalies is inconsistent with the Efficient Market Hypothesis (EMH) (Fama, 1970), at least in its weak-form sense and suggests that new and alternative market equilibrium models may be needed. The EMH postulates that investors are not able to earn above-average returns because security prices follow a random walk meaning that current prices reflect all the information available. However, the presence of the calendar anomalies implies the existence of seasonal predictability, and that investors could develop trading strategies in order to produce systematic abnormal profits based on those patterns. Nevertheless, many times the risk involved can be significant and the transaction costs are substantial, making the investment not rewarding. Schwert (2003, p. 942) notes that *"if anomalous return behaviour is not definitive enough for an efficient trader to make money trading on it, then it is not economically significant*".

Among many seasonal patterns, the most studied anomalies are the January effect (e.g., Rozeff and Kinney, 1976; Gultekin and Gultekin,1983; Easterday et al., 2009), the Halloween effect (e.g., Bouman and Jacobsen, 2002; Jacobsen and Visaltanachoti, 2009), the Pre-Holiday effect (e.g., Lakonishok and Smidt, 1988; Ariel, 1990; Cadsby and Ratner, 1992; Kim and Park, 1994), the Turn-of-the-month effect (e.g., Ariel, 1987; Jaffe and Westerfield, 1989; Agrawal and Tandon, 1994; Marquering et al., 2006; McConnell and Xu, 2008), and the Day-of-the-week effect (e.g. Cross, 1973; French, 1980; Rogalski, 1984; Jaffe and Westerfield, 1989; Chang et al., 1993; Connolly, 1989; Brusa et al., 2000; Dicle and Levendis, 2014).

Although there are many papers that support the existence of seasonal anomalies, the empirical evidence is mixed, depending on several factors. According to Zhang and Jacobsen (2013, p. 1745), *"whether or not these anomalies do exist, is in the eye of the beholder, and depends strongly on the sample used and which criteria are applied"* (e.g., on how one weights the statistical evidence and if one expects to be robust across different estimation techniques). Further, some studies are sceptical and point out problems of data mining, sample selection bias and noise (Kunkel et al., 2003; Maberly and Pierce, 2003; Maberly and Pierce, 2004; Lucey and Zhao, 2008).

According to Lakonishok and Smidt (1988), the best way to avoid these issues is to use long and new data. The author also mentions that it is necessary to analyse at least 90 years of data in order to detect monthly anomalies and obtain reliable estimates. Also, larger data samples are crucial to assess whether the anomalies change over time or if these persist throughout ages (Zhang and Jacobsen, 2013). However, only few studies scrutinize long periods (e.g., Lakonishok and Smidt, 1988; Zhang and Jacobsen, 2013), and the remaining papers typically analyse approximately 10 to 50 years of data.

Likewise, in spite of many monthly seasonal anomalies have been identified, few papers have documented the behaviour of these calendar anomalies and their persistence over time. Agrawal and Tandon (1994) and Marquering et al. (2006) report the decline, disappearance or even the reversal of some of these anomalies, particularly after the first studies of each seasonal pattern were published. Normally, once price patterns are identified, the market reacts efficiently by trading them out of existence (Schwert, 2003; Kunkel et al, 2003). Still, some studies noticed that anomalies persist and present in today's stock markets (e.g., Zhang and Jacobsen, 2013 and Siegel, 2014).

In the Portuguese stock market, there is no consensus on the presence of seasonal effects. For instance, some authors found more significant results for the month of January (Silva, 2010), but others found in March (Fountas and Segredakis, 2002), others in February (Silva, 2010), others in June (Silva,2010; Lobão and Lobo, 2018), others in September (Silva, 2010) and others in December (Silva, 2010; Lobão and Lobo, 2018).

The objective of this study is to analyse whether calendar anomalies exist in the Portuguese stock market over the period 1900-2020, being that the 1900-1988 period corresponds to new historical data, not yet explored. To the best of our knowledge, in the present moment, this is the most comprehensive study both regarding the number of techniques used and the extension of the period under analysis in the study of calendar anomalies in Portugal. We will investigate whether several seasonal anomalies observed in the literature subsists in the Portuguese exchange market, how anomalies behave over time, if investors can take advantage of these return patterns through the development of several trading strategies and implementing a data-snooping resistant test, the "*Superior Predictive Ability*" test (Hansen, 2005).

Therefore, the dissertation expands the existing literature in numerous ways. First, we study an underexplored market, filling a gap in the literature. Second, as previously mentioned, this is the most complete study to date regarding the extension period under scrutiny and the number of techniques applied in the investigation of seasonal anomalies in the Portuguese stock market. Thus, we examine the behaviour and performance of calendar anomalies and at the same ensure that our results are robust. Third, unlike what happens in similar studies which focus on long time series, we investigate a broad set of seasonal patterns. For instance, we are the first to inquiry about the existence of the Halloween effect, quarterly, semi-annual and weekly seasonality patterns. To end, it is one of the few studies that assesses the economic significance through the data-snooping resistant strategies simulation based on Hansen's (2005) "*Superior Predictive Ability"* test (or SPA test).

Regarding the presence of seasonal anomalies, our OLS results show a significant January, September, April, and Halloween effect. Nevertheless, the prevalence does not subsist over all subperiods. Additionally, there is consensus when comparing with other methodologies applied. In particular, the evidence on the annual t-statistics does not support the existence or prevalence of any calendar pattern. Overall, our results suggest that the presence of calendar anomalies depends on the "*eye of the beholder*". Moreover, according with the "*Superior Predictive Ability"* test, the January and Halloween strategies cannot surpass the buy-and-hold benchmark.

This dissertation is divided into six chapters. After the current introductory part, the second chapter briefly presents a literature review of the calendar effects. The third chapter postulates the data and the fourth chapter, the econometric methodology that will be applied in the empirical exercise. Following that, chapter 5 presents and discusses the empirical results. Finally, chapter 6 sums up the main findings and conclusions.

2. Literature Review

A vast literature on the presence of patterns in stock returns has been uncovered over the last decades. These studies are conducted in different regions and time periods, and also apply different estimation techniques. The following literature review includes a brief overview of the main empirical findings and explanations provided in the literature.

2.1 Monthly Calendar Effects

The January effect has been one of the most extensively studied seasonal anomalies. The calendar effect is the tendency of stocks to exhibit a higher return than the return during the remaining months of the year. Often, this anomaly is also associated with the Turn-of-the-year effect which is described by the increase in stock prices during the last days of December and on the first days of January (Roll, 1983; Lakonishok and Smidt, 1988).

Despite this calendar anomaly was initially brought to the attention of modern finance by Rozeff and Kinney, it was firstly introduced to the academic literature by Wachtel[1](1942). In a seminal article, Rozeff and Kinney (1976) using an equal-weighted index of NYSE prices, reported that from 1904 to 1974, the average return during the month of January appeared to be 8.0 times higher than returns for a typical month (the average return during the month of January was 3.48 percent, compared to only 0.42 percent per month for the remaining eleven months). Afterwards, Gultekin and Gultekin (1983) discovered that the effect is not only pronounced in the US, but also among 17 of the most industrialized countries from 1959 to 1979.

Further studies noted that this pattern is particularly strong for small capitalization companies[2] (e.g. Banz, 1981; Reinganum, 1983; Fama, 1991). Similarly, Siegel (2014) analyse the period from 1925-2006, and the empirical evidence supports this reasoning since the average arithmetic return on the S&P 500 Index in the month of January was 1.57 percent, while the average returns on the small stocks came to 6.07 percent. The results shown that large stocks were only able to outperform small stocks in 16 years over the period under analysis. Nevertheless, the author mentions that in foreign markets, the January effect is significantly present in large stocks. Kohers and Kohli (1991) shown the presence of the

[1] According to Zhang and Jacobsen (2013)

[2] According to Baker and Wurgler (2007), low-capitalization stocks are more affected by sentiment, and this in turn is related with the intensification of the anomalies (Stambaugh et al., 2012).

January effect in the S&P 500, during the period from 1930 through 1998, and in a more recent period Easterday and Sen (2016) observe this pattern in the period between 1991 and 2011.

Meanwhile, some scholars have doubts about the significance of the January effect and some recent analysis support a decline or the disappearance of the anomaly. For instance, Fountas and Segredakis (2002) examined 18 emerging markets in the 1987-1996 period and point out the lack of results in favour of the January effect[3]. However, they found evidence of seasonal effects for several markets, as in the case of the Portuguese stock market where the authors observed statistically significant positive March returns and a negative June return.

Similarly, Marquering et al. (2006) observed a decline and a trend towards zero following the publication of Rozeff and Kinney's (1976) paper, being that the anomaly does not exist anymore in stock returns. In more recent studies, Siegel (2014) mentioned that the January effect weakened in recent years. Darrat et al. (2011)[4] and Patel (2016) noticed that the January effect is no longer present in international stock returns.

Other researchers argue that the January effect continues to exist in the stock market, particularly in the United States. Haug and Hirschey (2006) analysed the period starting in 1802 until 2004 to show that the effect persisted in the U.S. for small-cap stocks in equal-weighted returns until the last years of the sample. More recently, Easterday et al. (2009) concluded that the January effect persists over a long period, from 1946 to 2007, and find no evidence that the January premiums are declining. Siegel (2014) confirms these conclusions and mentioned that the January effect prevailed even during the most powerful bear markets. In the United Kingdom, Zhang and Jacobsen (2013) investigated stocks prices returns during 300 years starting in 1693 and found a robust January effect but when conducting an investigation under the subperiods, January effect only turned to significantly positive around 1830[5] being that in the first 100 years it was significantly negative.

The relationship between the January effect and other factors was examined by several authors. Some of the causes proposed to justify this phenomenon where: (*i*) tax-loss selling

[3] Except for Chile.
[4] Except for Denmark, Ireland and Jordan.
[5] Ariel (1990) note that the Turn-of-the year studies must consider holiday effects. In fact, Zhang and Jacobsen (2013) confirmed this because the Turn-of-the-year effect only became distinguished as Christmas become more popular.

hypothesis; (*ii*) "window dressing" hypothesis; (*iii*) the information hypothesis; (*iv*) the liquidity hypothesis and (*v*) optimistic expectations hypothesis. The most common explanation is the tax-loss selling hypothesis (e.g. Reinganum, 1983; Roll, 1983, Poterba and Weisbenner, 2001; Starks et al., 2006) states that at end the year, there may be a decline in stock prices because investors sell stocks that have experienced a decline in price over the year, thus recording capital losses to reduce the amount of tax to pay. Subsequently, in January investors repurchase the stocks at a lower price, causing abnormally high January return (Sias and Starks, 1997). However, this is not a complete explanation as the January effect exists prior to income taxation (Chan, 1986), in countries where the fiscal year does not start in January (e.g. Australia) (Gultekin and Gultekin, 1983), and in countries that do not have a capital gains tax (e.g., Canada before 1972 and Japan before 1989) (Berges et al.,1984).

Concerning the alternative explanations, the window dressing hypothesis refers that the January effect may be caused by the trades of the institutional investors at year-end and this is normally the moment of their portfolio holdings disclosure (Haugen and Lakonishok, 1988; Lakonishok et al., 1991). These investors tend to buy stocks with positive priors returns ("winners") and sell stocks with negative prior returns ("losers") to present attractive year-end portfolio holdings and impress their clients. After the holding disclosure, investors repurchase their stocks. The information hypothesis (Rozeff and Kinney, 1976; Keim, 1983) suggests that this phenomenon is caused by an unsuitable modelling risk. There is a lot of important information that is being released during this period and the market fail to account for the increased uncertainty associated. In addition, the January effect can be caused by risk (Rogalski and Tinic, 1986; Garrett et al., 2005)

There is also the liquidity hypothesis, in which Ogden (1990) proposed that investment decisions tend to be made in January and argued that the January effect came from the increased demand for stocks caused by the "extra cash" that investors receive at year-end from "*holiday*" payments (e.g. salaries, bonuses and dividends). The final hypothesis is associated with psychological factors. For example, Ciccone (2011) refers that the turn of the year is a time of "renewed optimism" that lead to an increase of the stock price in January.

Aside from the January anomaly, there has been reports of a related anomaly, the December Effect (Clare et al., 1995; Singal, 2006; Darrat et al., 2011; Zhang and Jacobsen, 2013), which lies on high December returns, usually justified as a result of tax-gain selling. According to Chen and Singal (2003), investors postpone realization of capital gains and, consequently the payment of taxes. Therefore, investors only sell winner stocks in January, so the selling pressure on winners should be small in December, triggering the price of winners to rise.

In the Portuguese stock market, results refute the presence of the January effect (Balbina and Martins, 2002; Fountas and Segredakis, 2002; Darrat et al., 2011; Lobão and Lobo, 2018). Only Silva (2010) that looked at the main stock indexes of Portugal (BVL-Geral and PSI20-Total Return) in the period 1989-2008, reached to a weak Turn-of-the-year effect, since the three best mean monthly returns belonged to December, January and February, however, the statistical evidence was fragile. Nonetheless, Lobão and Lobo (2018) pointed to the existence of statistically significant positive risk premiums in December.

Lastly, there is the following popular market wisdom idea "*As goes January, so goes the year*", which means that January gives a valuable signal for the following 11 months of the year. Outside the US market, there is very limited evidence supporting this pattern (Easton and Pinder, 2007; Bohl and Salm, 2010).

2.2 Halloween Effect

The Halloween Effect, or the Sell-in-May-effect is an equity return anomaly in which the summer months (May through October) provide higher returns when compared to winter months (November through April). This pattern is also associated with the old market strategy, "*Sell in May and go away*" which suggests that investors should not invest in the stock market during summer months.

In their seminal paper, Bouman and Jacobsen (2002) discovered this calendar anomaly by analysing stock returns across 37 countries from January 1970 through August 1998 and found the anomaly in 36 of these markets under scrutiny, including both developed and emerging markets. As well, the effect proves to be robust over time and the mentioned strategy has economic significance. The authors further noted that it is particularly strong in European countries, does not appear to be caused by data mining, neither is related to risk differences, and that the anomaly is not driven by the January effect (expect for the US). These authors also found that the Halloween trading strategy provided higher returns than the buy-and-hold in all countries except Hong Kong and South Africa. However, volatility (a measure of risk) was higher in the Halloween trading strategy.

Since then, many studies further confirmed the existence of the Halloween effect. For instance, Jacobsen and Visaltanachoti (2009) investigated the US stock market sectors over the 1926–2009 period and found that the Halloween effect affected almost all companies from different industries being that this pattern was statistically significant in more than two-thirds of those sectors. In the recent past, Andrade et al. (2013) confirmed the persistence of the Sell-in-May effect by re-examining Bouman and Jacobsen (2002) findings, investigating the same group of stock markets but adding new data from 1998 to 2012.

However, some doubts on the existence of the anomaly have been reported (Maberly and Pierce, 2003; Maberly and Pierce, 2004; Lucey and Zhao, 2008; Zhang and Jacobsen, 2013; Dichtl and Drobetz, 2015). Using S&P 500 futures contracts as a benchmark index, Maberly and Pierce (2004) evidence did not support a Halloween effect in the US for the 1982-2003 period. The authors argued that the Bouman and Jacobsen's results might be caused by data outliers[6]. Subsequently, Haggard and Witte (2010) criticised this study and applied a robust regression technique that restricted the influence of outliers. Thus, it was found that the Halloween effect is robust from outliers and significant for the period of 1954–2008.

Furthermore, Lucey and Zhao (2008) while analysing this effect in US CRSP data, found a weak Halloween effect for the US market and propose that it may just be a reflection of the January anomaly. Zhang and Jacobsen (2013) studied more than 300 years of UK stock returns and found a positive Halloween effect, but the magnitude of the effect shifted over time and depended on the sample subperiod.

More recently, Zhang and Jacobsen (2021) conducted a worldwide study, including Portugal as a country under analysis, comprising all historical data available and found that the Halloween effect was robust and exploitable when comparing with the buy-and-hold strategy even after the publication of Bouman and Jacobsen (2002) study. On average, across the world, returns between November to April were 4% higher than for the months of May to October. However, the study omits transaction costs in their simulations which adversely impacts the Halloween strategy profitability when comparing with the benchmark performance.

[6] October 1987: World equity prices crash; and August 1998: Collapse of the hedge fund Long-Term Capital Management

Lloyd et al. (2017) analyses 35 of the original countries from Bouman and Jacobsen (2002) and also found that the Halloween effect was robust in 34 countries during the 2007-2015 period. The authors also mention that this anomaly has strengthened rather than weakened in the recent years. Therefore, according to the mentioned studies, the Halloween effect does not appear to follow the theory, as calendar anomalies tend to disappear or to vanish after being discovered (Schwert, 2003).

Nonetheless, Dichtl and Drobetz (2014) analysed six total return stock indexes (S&P 500, euro Stoxx 50, Dax 30, CAC 40, and FTSE 100) and implemented the data-snooping resistant *"Superior Predictive Ability"* test (Hansen, 2005). Results shown that the Halloween effect has weakened or even disappeared at the end of the period under scrutiny, in 2012, which is now not economically significant. Dichtl and Drobetz (2015) also reported similar results for the United States.

Some research points to a similar seasonal pattern, the September Effect that can be described by negative mean returns in September when comparing with the rest of the year. In fact, Siegel considered September as the worst month of the year and in the U.S. is the only month with negative returns. Likewise, it is the worst month in 17 of the 20 countries analysed and in all the main world indexes, including the EAFE Index and the Morgan Stanley all-world index. (Siegel, 2014). Furthermore, analysing the DIJA, from 1885 to 2006, it appears that despite the September Effect has not prevailed since 1990, it is becoming stronger over the past 16 years (Siegel, 2014).

Clare et al. (1995) confirmed this effect for the 1955-1990 in the UK equity market, but, Zhang and Jacobsen (2013) corroborate the previous findings. Despite September being the month with the lowest returns for the 1951-2009 period, this pattern is not consistent because actually September mean returns are higher in some subperiods. Furthermore, Siegel (2014, p.315) points out as an explanation for this effect, the possibility that family's need to sell shares in order to pay for vacations and school expenses.

Concerning the explanations proposed for the Halloween effect, Bouman and Jacobsen (2002) highlighted the importance of vacations because lower summer returns may be related to the changes that holidays cause in risk aversion and in liquidity. Bouman and Jacobsen (2002) notes that "*the size of the effect is significantly related to both length and timing of vacations and also to the impact of vacations on trading activity in different countries*". Also, a recent study of 34 countries by Jacobsen et al., 2019 found support for vacation behaviour, especially among European countries. Other popular explanation is related to the winter temperature changes (e.g., Hirshleifer and Shumway, 2003; Cao and Wei, 2005) and the Seasonal Affective Disorder hypothesis, proposed by Kamstra et al. (2003) that concerns the depressing effect derived from lack of daylight. However, this study has been criticized in a number of papers for its methodological flaws (e.g., Jacobsen and Marquering, 2008). This is also a good justification for the September findings but this hypothesis does not explain why September has poor return in Australia and New Zealand, where Spring and long days are starting.

In the Portugal stock exchange, Silva (2010) found that September and June (negative in all subperiods) were the worst months and Lobão and Lobo (2018) found an insufficient market risk premium during the month of June for the 1989-2012 period. This negative June return was also observed in Fountas and Segredakis (2002) paper.

2.3 Week-of-the-year effect

The Week-of-the-year effect, a less popular anomaly among scholars, is the tendency of stocks to exhibit abnormal returns on one particular week when compared to the remaining weeks of the year. Research document Levy and Yagil (2012) used the weekly rates of returns on the stock market for 20 countries under the period 1950-2008. Results revealed that week 44 (which correspond to the period October 29 and November 4) is positive in 19 of the 20 countries and statistically significant in 18 countries. In contrast, the returns for week 43 (which correspond to the period between October 22 and October) are negative and statistical evidence for the 19 of the 20 countries to be studied. The authors also argue that the results appear to be consistent with the Halloween effect and the Seasonal Affective Disorder hypothesis (Kamstra et al., 2003).

3. Data

In this chapter, we will expose our data and a summary of the descriptive statistics.

3.1 Data Collection and Sources

To empirically evaluate the presence of calendar anomalies on the Portuguese stock market, the data used in this study consists of monthly returns in the period 1900 until 2020, with the exception of two months at the beginning of WWI[7]and during approximately three years following the April 1974 military coup.

We have also split the data into several smaller subperiods in order to clearly understand the behaviour of the calendar anomalies, detect any trend and persistent patterns over time, study the potential effects of samples sizes on monthly stock returns and to obtain robust statistical testing (Zhang and Jacobsen, 2013). In particular, the 1989-2010 subperiod allows us to compare the results with previous Portuguese studies (e.g., Balbina and Martins, 2002; Fountas and Segredakis, 2002; Darrat et al., 2011; Lobão and Lobo, 2018).

In order to examine if the week-of-the-year anomaly (Levy and Yagil, 2012) is present in the Portuguese stock market, we have broken down each year into 53 weeks. The first week corresponds to the period between January 1 and ends on January 7, the second week begins on January 8 and ends on January 14, and so on. The only week that contains less than 7 days is week 53.

The monthly stock returns were gathered through different sources. Until 2015, we use the database from the book "*The Lisbon Stock Exchange in the Twentieth Century*" (Mata et al., 2017). This database is available online in excel format[8]. Further, the data is also integrated in Dimson, Marsh and Staunton (DMS) database (commercialized by Morningstar), the authors of the book "*Triumph of the Optimists: 101 Years of Global Investment Return*" (Dimson et al., 2009).

The authors of "*The Lisbon Stock Exchange in the Twentieth Century*" (Mata et al., 2017) developed a share index using a methodology that makes the index comparable to common

[7] We have adopted the filling forward method and considered the monthly price in August and September 1914 equal to July 1914. We have also applied the same reasoning during the preparation of the weekly data. In this case, the weeks in August and September 1914 assume the values of the last week of July 1914.

[8] Available in https://www.uc.pt/imprensa_uc/Lisbon_Stock_Anexo_Estatistico/n. Visited in October 2020.

international indices and "*the new time series from 1900 replicates as closely as possible the methodology of the BVL-General index of the Lisbon Exchange for the entire century.*" (Mata et al., 2017, p.71).

The estimated capitalization-weighted index comprises 3 segments (Mata et al., 2017, pp. 73-74):

- From the end of December 1899 until April 24, 1974;
- From January 1978 until December 1987;
- From January 1988 to December 2013.

Until 1987, the main source of numerical data was the collection of Daily Bulletins published by the Lisbon Stock Exchange available in the Documentation Centre of the Lisbon Exchange (now called Euronext Lisbon) (Mata et al., 2017). Prices were retrieved once a week, normally on Wednesday to avoid the weekend effect.

Thereafter, from January 5, 1988, the information used to construct the index refers to the BVL Geral (BVLG) / PSI-Geral. This is a capitalisation-weighted price index computed as the average of the daily close prices and composed by the eligible companies listed on the Eurolist by Euronext Lisbon.

Despite stock prices were collected on a daily close-to-close basis, the authors needed to convert to weekly data in order to make the data comparable. Since this database only includes data until April 22th, 2015, it was necessary to complete it until December 31, 2020. For such, we have collected the data from Thomson Reuters Datastream. Subsequently, we convert the weekly data into monthly data using the method described by Martinovića et al. (2016).

Some studies (e.g. Timmermann and Granger, 2004; Cochrane, 2017) mention that it is important to consider time-varying risk premiums arguing that efficiency tests should take this market characteristic into account. Therefore, we will also analyse the risk premiums in the regression approach, as an additional robustness check (e.g., Zhang and Jacobsen, 2021). The monthly risk premium has been estimated by subtracting the monthly risk-free interest rate from the total monthly return.

As a proxy for the risk-free interest rate, we used the database of Mata, Costa and Justino database from the book "*The Lisbon Stock Exchange in the Twentieth* Century" (Mata et al., 2017) which comprises short-term interest rates. Once again, the database needed to be completed. We used as a proxy the reference interbank interest rate of the euro money market for the overnight term (EONIA) following the approach of Costa et al. (2012). EONIA was obtained through EURIBOR online statistics database[9].

Returns were computed as continuous returns:

$$R_t = \ln\left(\frac{I_t}{I_{t-1}}\right) * 100 \tag{3.1}$$

Where R_t stands for the natural logarithmic return of the index on date *t*; and It and $It-1$ are closing values on date *t* and $t-1$.

3.2 Descriptive Statistics

Table 1 contains a summary of the key descriptive statistics (mean, standard deviation, skewness, and kurtosis) of the monthly returns for each calendar month. Since the return from January 1978, -174.961% is an extreme value and significantly impacts the empirical results, we will adjust the data under analysis and omit this observation from now on. A more detailed set of descriptive statistics appears in Appendix A.

TABLE 1 – DESCRIPTIVE STATISTICS OF CALENDAR MONTHS

	Obs.	Mean	Std. Dev.	Skew.	Kurt.
Mean Monthly Return	1406	**0.010**	0.052	1.622	24.623
January	116	**0.029**	0.072	5.482	44.455
February	118	**0.016**	0.054	-0.378	6.667
March	118	0.010	0.048	-1.016	7.348
April	118	**0.017**	0.049	2.333	14.279
May	117	0.007	0.044	1.485	5.071
June	117	-0.001	0.040	0.49	0.935
July	117	-0.005	0.039	0.518	6.21
August	117	0.009	0.043	0.95	7.541
September	117	**0.019**	0.058	3.084	21.096
October	117	0.006	0.060	1.097	7.889
November	117	0.005	0.052	-3.346	24.057
December	117	0.006	0.053	-1.051	20.621

Notes: Table 1 reports average return, standard deviation, skewness and kurtosis for each calendar month. Values reported in **bold** denote above average monthly returns
Source: Own elaboration

Concerning the monthly average returns, although the average monthly return over the entire sample is only 1.00%, when analysing smaller periods, in particular the 20-year subperiods, it is possible to observe an upward average return over time, reaching the highest average return (1.30%) in the 1978-2000 subperiod. Nevertheless, please note that in this period, the

[9] Available in https://www.euribor-rates.eu/en/eonia/

standard deviation is also relatively higher (0.9%), and therefore, there is a higher risk in investing (assuming that the standard deviation is a measure of risk). Unlike the remaining subsamples, the last 20-years subperiod (2001-2020) reveal the lowest monthly average return.

We also find that the average returns are especially high in January (2.9%), September (1.90%); April (1.70%) and February (1.6%). Recently (2001-2020), April is the month with the highest average return at 5% level. However, the statistical evidence does not seem to persist throughout the earlier subsamples. Based on the literature, the empirical result is not surprising for April. Gultekin and Gultekin (1983) identified this April effect in the UK stock market, attributing to the fact that the deadline for companies to disclose their annual reports is in March for many countries (tax-loss selling hypothesis).

Despite the popularity of September being the most dreaded month, the title of worst calendar month should go to July (-0.5%) and June (-0.1%). Even though several subperiods were associated with negative July average returns, in the recent 2001-2020 subperiod, the average return is positive (0.3%).

Volatility varied from month to month and was the highest in January (7.2%), October (6.00%) and September (5.8%) and the lowest in June and July (4.0% and 3.9%, respectively). One of the most common explanations for the presence of the calendar anomalies is to justify that the higher returns obtained are a compensation for the additional risk that investors are bearing during those periods (e.g. Bouman and Jacobsen, 2002). The higher return observed in January suggests that it might be a compensation of risk.

Concerning the Halloween effect, as disclosed in Table 2, monthly mean returns for the November-April period surpasses the mean returns for the May-October period. Additionally, it is also possible to observe that in the last 20 years of the sample, the returns are even negative between May-October which means that is the investor would better off not investing in the market. Analysing the trade-off between risk and return, the difference in the standard deviation in the two subperiods is minimal and the mean return is relatively higher in the winter months. Therefore, it is not likely that the Halloween effect arises due to the risk difference.

TABLE 2 – DESCRIPTIVE STATISTICS OF SUMMER AND WINTER MONTHS

	Obs.	Mean	Std. Dev.	Skew.	Kurt.
May-Oct	704	0.006	0.049	1.699	12.849
Nov-Apr	702	0.014	0.056	1.527	31.011

Notes: Table 2 reports average return, standard deviation, skewness and kurtosis for the winter months (November through April) and summer months (May through October). **Source:** Own elaboration

Further, Table 3 and Table 4 shows the descriptive statistics for the quarters and semesters of the year. The first quarter and first semester of the year display the highest average monthly return. Nevertheless, standard deviation is also higher.

TABLE 3 – DESCRIPTIVE STATISTICS OF SEMESTER MONTHS

	Obs.	Mean	Std. Dev.	Skew.	Kurt.
1st semester	704	0.013	0.053	2.738	31.488
2nd semester	702	0.007	0.052	0.438	17.028

Notes: Table 3 reports average return, standard deviation, skewness and kurtosis for each semester of the year. **Source:** Own elaboration

TABLE 4 – DESCRIPTIVE STATISTICS OF CALENDAR QUARTERS

	Obs.	Mean	Std. Dev.	Skew.	Kurt.
1st quarter	352	**0.018**	0.059	3.070	36.242
2nd quarter	352	0.008	0.045	1.647	8.942
3th quarter	351	0.008	0.048	2.268	18.550
4th quarter	351	0.006	0.055	-0.786	15.632

Notes: Table 4 reports average return, standard deviation, skewness and kurtosis for each quarter of the year. Values reported in **bold** highlights the highest quarter return**. Source:** Own elaboration

Lastly, the main evidence found in the week analysis is that the average weekly return is low (0.2%) and the standard deviation is relatively high (4.9%).

TABLE 5 – DESCRIPTIVE STATISTICS OF WEEKLY RETURNS

	Obs.	Mean	Std. Dev.	Skew.	Kurt.
Weeks	6215	0.002	0.049	-0.145	34.525

Notes: Table 5 reports average return, standard deviation, skewness and kurtosis for each week of the year. **Source:** Own elaboration

Finally, findings demonstrate that there is a positive skewed pattern in the returns distribution. The high values of Kurtosis reflect the impact of outliers.

4. Methodology

This section discloses the choice of the formal set of econometric techniques applied during the study of the calendar anomalies in the Portuguese stock market.

4.1 Standard Methodology

The standard methodology to examine the evidence of calendar anomalies consists in a regression approach where returns are regressed on a series of dummy variables that represent the time period of interest (e.g., Barone, 1990; Wilson and Jones, 1993; Mehdian and Perry, 2001; Bouman and Jacobsen, 2002; Darrat et al., 2011; Bouges et al., 2009; Zhang and Jacobsen, 2013; Lobão, 2018). The regressions are going to be computed following the standard Ordinary Least Squares (OLS) methodology with the Newey-West standard deviations (1987) in order to adjust for heteroskedasticity and autocorrelation (HAC estimator).

The monthly anomalies will be tested using the following regression (Borges, 2009; Zhang and Jacobsen, 2013; Urquhart and McGroarty, 2014):

$$R_t = \alpha_0 + \beta_i D_{it} + e_t \tag{4.1}$$

Where, R_t equals the natural logarithmic monthly return of the total index on date *t*. D_{it} is the dummy variable that assumes the value 1 when the calendar effect conditions is verified and 0 otherwise.

- D_{it} is the dummy variable for a particular month;
- D_{it} is the dummy variable for that equals 1 if month *t* falls in the period from November through April;
- D_{it} is the dummy variable for a particular quarter;
- D_{it} is the dummy variable for a particular semester.

α_0 is the constant and e_t is the error term. $\beta_i$shows the magnitude of the difference between the mean return of the *month(s)/semester(s)/quarter(s) and week(s)* of interest and the mean return of the remaining *month(s)/semester(s)/quarter(s) and week(s)* respectively.

For the weekly effect, R_t equals the natural logarithmic weekly return of the index on date *t*. D_{it} is the weekly dummy that equals 1, for the corresponding week *t* of the year (*t*=1,…,53).

Please note that the most common approach of modelling the calendar effect in stock market indexes is by estimating, for instance in the test of the monthly calendar anomalies, the subsequent equation:

$$R_t = \alpha_1 + \beta_2 D_{2t} + \ldots + \beta_{12} D_{12t} + e_t \tag{4.2}$$

However, Borges (2009) points out that this specification reveals through β_2 whether February returns differ significantly from January average returns but cannot compare February with the remaining months. Borges (2009) noted that if the sample size is considerably large, the t-test is biased towards accepting positive excess returns and against accepting negative excess returns. Therefore, equation 4.1 is the most appropriate.

4.2 Time-varying behaviour of the Calendar Anomalies

One of the most common approaches to evaluate how calendar anomalies vary (behave) over time is through the analysis of seasonal patterns throughout different subperiods. Thus, we will regress several OLS regressions with the HAC estimator over several periods.

Even with the subsample analysis, the choice of size of the subsample is subjective and as Urquhart and Hudson (2013) arguments, this contains the risk that one extreme event could skew the results for many subsamples.

Therefore, we will investigate how the stability of the coefficients evolve with time through the OLS rolling windows regression approach (e.g. Zhang and Jacobsen, 2013; Urquhart and McGroarty, 2014). The use of rolling window technique in the estimation of model coefficients is recent in the study of calendar anomalies (Zhang and Jacobsen, 2013; Urquhart and McGroarty, 2014; Bampinas et al., 2016; Zhang and Jacobsen, 2021). A rolling window regression implies estimation of the regression equation several times to obtain the estimated value of β that changes over time. Therefore, this procedure discloses the behaviour of the calendar anomalies and ensures that our coefficients estimates are not sample dependent (Sullivan et al., 2001). We conduct a 20-year rolling window OLS regression (window 252 and step 12) for each of the calendar months and Halloween effect. Thus, we are able to explore the seasonal patterns found in greater detail.

Further, we will also employ a dynamic analysis which consists in the examination of the time series t-statistics, following Marquering et al. (2006) paper. The authors provided a detailed study on the behaviour of the calendar anomalies (conception, continuation, and potential disappearance). We will obtain the annual t-statistics through equation 4.1.

4.3 Robustness Checking

To check the robustness of the results, we measure the potential existent patterns on risk premiums using the standard OLS methodology and Newey-West (1987) standard deviation (e.g. Zhang and Jacobsen, 2013; Lobão and Lobo, 2018; Zhang and Jacobsen, 2021). Therefore, we have adapted equation 4.1, as stated below.

$$(R_{it} - R_{ft}) = \alpha_0 + \beta_i D_{it} + et \tag{4.3}$$

Where the $(R_{it} - R_{ft})$ is the risk market premium on month *t*. The remaining equation terms where already provided in section 4.1.

When examining calendar anomalies through the OLS regression, possible econometric issues may arise due to the characteristics of stock returns such as volatility clustering. To ensure robust and unbiased results, we re-examine the calendar effects through the Generalized Conditional Heteroscedastic (GARCH) model (e.g. Brooks and Persand, 2001; Choudhry, 2001; LEaN, 2011; Zhang and Jacobsen, 2013; Georgantopoulos and Tsamis, 2012; Zhang and Jacobsen, 2021) in order to capture the impact of volatility and incorporate heteroscedasticity into the estimation procedure since it allows variances of error terms to be time dependent. Therefore, we can draw some conclusions regarding the impact of clustering volatility and evaluate the strength of the previous results.

As Engle (2001) suggests, GARCH (1,1) model is the simplest and is the commonest robust model. In turn, the specification is presented as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \sigma_{t-1}^2 \tag{4.4}$$

Where σ_t^2 and σ_{t-1}^2 are the conditional variance of stock returns at time *t* and *t-1*, ε_{t-1}^2 are squared unexpected returns for the previous periods, μ is the constant term, α and β are coefficients.

In order to avoid spurious outcomes, we use the non-parametric Kruskal–Wallis (KW) test as the GARCH model is not able to capture the non-normality of data (Urquhart and McGroarty, 2014; Khuntia and Pattanayak, 2021). The Kruskal–Wallis test examines if the populations from which the samples are drawn have identical distributions and the test is particularly sensitive to differences in means. Therefore, we examine the differences between the returns on various calendar effect returns to those months which are not calendar effect months. The statistic test equation is:

$$H = \left(\frac{12}{N\,(N+1)} \sum_{j=1}^{k} \frac{R_j^2}{n_j}\right) - 3N(N+1) \tag{4.5}$$

Where R_j^2 is the average rank of observations in the j^{th} group, n_j is the total number of observations in the j^{th} group, k is the number of groups and N is the total number of observations.

Finally, outliers can be the justification for the presence of the calendar effects. In line with Zhang and Jacobsen (2013) and Haggard and White (2010) studies, we also perform an additional test of robustness by applying an OLS robust regression in order to determine the significance of the calendar anomalies after controlling for extreme returns.

Therefore, robust regressions are computed through M-estimation introduced by Huber (1973) which is considered appropriate when the dependent variable contains outliers. M-estimators reduce the influence of extreme errors by applying reduced weights to larger squared errors. Nonetheless, by imposing the specific structure on the conditional heteroscedasticity, some observations can be excluded and are not outliers.

4.4 Interaction between Calendar effects

Calendar anomalies are often related to other return effects. Several studies (Bouman and Jacobsen, 2002; Mayberly and Pierce, 2004; Lucey and Zhao, 2008; Haggard and Witte, 2010) demonstrate whether the presence of the Halloween Effect anomaly results from the above average returns reported during the month of January. For instance, Lucey and Zhao (2008) examined U.S. stock data from 1926 to 2002 and argued that the Halloween effect could simply be a reflection of January hypothesis and not a distinct anomaly.

Therefore, we will examine whether the difference of average returns between summer and winter months is due to the high performance of January. To formally test this possibility, we will analyse the robustness of the Halloween effect considering the January effect using the following equation:

$$R_t = \alpha_0 + \alpha_1 D_{Halt} + \alpha_2 D_{Jant} + et \quad (4.6)$$

Where D_{Halt} is a dummy variable which takes the value 1 if month *t* falls into the time interval from November to April, excluding January. The additional dummy variable, D_{Jant}, captures a potential January effect; this variable takes the value of 1 in January (and 0 otherwise).

Hence, if the Halloween effect is robust in the presence of the January effect, we should obtain a significant coefficient (α_1) on the winter dummy, even in the presence of the January effect. If, on the contrary, only the January effect is significant, then it will be possible to conclude that the effect initially described by Bouman and Jacobsen (2002) does not exist in Portugal and, therefore, the Halloween effect could actually be the January effect in disguise.

4.5. Performance analysis of the investment trading strategies

In a first step, we will examine the profitability of a strategy based on the buy-and-hold versus that on the Halloween indicator and on the January effect (e.g. Haggard and Witte, 2010; Zhang and Jacobsen, 2013; Urquhart and McGroarty, 2014). The Halloween strategy (also known as the "*Sell in May and Go Away*" strategy), posits that we must sell stocks in early May, invest in a risk-free asset and re-invest in stocks on late October. This is one of the most interesting strategies for investors since it can be implemented with low transaction costs.

The buy-and-hold strategy is named as a "*do nothing*" strategy in which the investor will hold the stock market portfolio throughout. This is based on the perspective that in long-term conditions, financial markets give a good rate of return even when considering a large degree of volatility.

The recent study from and Zhang and Jacobsen (2021) confirms Bouman and Jacobsen (2002) results and reveals that the payoff is higher for the Halloween trading strategy. The UK evidence reveals that investors with a long horizon would probably be able to beat the market since in a 5-year investment horizon, the chances for the Halloween strategy to exceed the buy-and-hold strategy were 80%, and for an investment horizon of 10 years, this odd increased to 90%.

Further, we will simulate the January effect strategy assuming an investment in the stock market during January and invest in a risk-free asset during the remaining months of the year.

Since some papers questioned to what extend is the success of a "good" forecasting model due to ability and not just luck (Sullivan et al., 1999, 2001). In order to avoid this type of issues, White (2000) developed the "Reality *Check*" (RC) method which allows the testing of possible superior performance of certain rules. Thus, we are able to compare the investing trading strategies not only against the benchmark but also to obtain statistical inferences from an empirical distribution of a performance measure by assessing all strategies, from which the best strategy is chosen (Dichtl and Drobetz, 2014).

However, Hansen (2005) warns that White's test can produce results that are too easily manipulated by the inclusion of poor and irrelevant models. In order to overcome this problem, Hansen (2005) developed the *"Superior Predictive Ability"* test (SPA test) with a similar framework to the RC, however the SPA test is considered more powerful and less sensitive to the inclusion of poor and irrelevant alternatives when compared to the RC test.

Therefore, we will reassess the calendar anomalies findings and account for the data-snooping bias problem (Lo and MacKinlay, 1990) using the SPA test[10] to verify if there is a strategy superior to the benchmark, namely the January effect or the Sell in and May and Go Away strategy.

Dichtl and Drobetz (2014) and Almeida et al. (2016) implemented the "*Superior Predictive Ability"* test. The first paper focused on the US and European stock market indices and in line with the predictions of the market efficiency, there is no investment strategy that significantly outperforms the buy-and-hold strategy. The second study focus on the Brazilian stock market. According with the empirical results, the Halloween strategy can surpass the buy-and-hold benchmark.

According with the information provided in Hansen (2005) and Dichtl and Drobetz (2014) papers, Hansen's test is based on real-valued loss functions. When evaluating trading strategies, an adequate loss function $L_{k,t}$ can be defined for model *k* as the negative continuously compounded return at time *t*, such that $L_{k,t} = -r_{k,t}$ (Hansen, 2005). The model forecasts are assessed in terms of their expected loss, E[L_k], measured as the mean value in the sample from $t = 1, \ldots, n$ (here, the mean negative return). The loss values are

[10] To operationalize the SPA test, we used a toolbox developed for Matlab by prof. Kevin Sheppard, available at http://www.kevinsheppard.com/MFE_Toolbox.

transformed into relative performance values, labelled $d_{k,t} = L_{0,t} - L_{k,t}$, where k=0 is the benchmark, k = 1,. . ., m forecasting models and t = 1, . . . , n.. In this case, the null hypothesis is that the outcome of the best trading rule is not better than the benchmark performance.

$$H_0 : \text{for } u_k = \mathrm{E}[d_{k,t}] \ll 0 \;\; \text{all k} = 1, \ldots, \text{m}. \tag{4.7}$$

Furthermore, the studentized test statistic is given by:

$$T_n^{SPA} = \max_{k=1,\ldots,m} \left[\frac{n^{1/2}\bar{d}_k}{\widehat{w}_k}, 0\right] \tag{4.8}$$

Where $\bar{d}_k = n^{-1} \sum_{t-1}^{n} d_{k,t}$ (average relative performance of model k), and $\widehat{w}_k{}^2$ is a consistent estimator of $\widehat{w}_k{}^2 \equiv var(n^{1/2}\bar{d}_k)$. As the distribution $n^{1/2}\bar{d}_k$ is unknown, but converges to a normal distribution, to operationalize the SPA test it will be necessary to implement the stationary bootstrap approach simulation of Politis and Romano (1994), which allows obtaining the p-values, as well as an upper bound and a lower bound. In order to proceed to proceed with the bootstrap simulation, we need to combine blocks with random lengths. The block length is selected to be geometrically distributed $q \in (0,1)$, resulting in a mean block length of q^{-1} (Dichtl and Drobetz, 2014).

In order to perform this test is necessary to define the investment strategies under analysis. The analysed monthly trading strategies are either invested 100% percent in the stock market or 100% percent in cash in a given month. When the investor is not exposed to the market, we assume that the investment is in a bank deposit earning the risk-free rate. Thus, the risk-free rate is the proxy for the return of the cash market. We include all possible = 4096 different monthly trading strategies in the implementation of the SPA-test, including the Halloween effect, but also for instance the January effect. The benchmark model (model 0) is the buy-and-hold strategy. Employing model 4095, we are constantly investing in cash during all 12 months in each year of the sample. We will generate 10.000 resamples through bootstrap and assume q=0.5 (Dichtl and Drobetz, 2014).

5. Empirical Results

In this chapter, we discuss the empirical results of the calendar patterns in the Portuguese stock market.

5.1 OLS Regression with Newey-West Standard Error Results

Table 6 presents the coefficient estimates and t-statistics based on Newey-West standard errors (1987) for each calendar month over the full sample and several subsamples.

TABLE 6 – CALENDAR MONTH EFFECTS: OLS REGRESSIONS

Sample Period	January		February		March		April	
	beta	**t-stat**	**beta**	**t-stat**	**Beta**	**t-stat**	**beta**	**t-stat**
1900-2020	**0.021**	**3.268*** **	0.007	1.419	-0.0002	-0.041	**0.008**	**1.808***
1900-1974	0.013	3.534***	0.005	1.398	0.003	0.731	0.006	1.398
1978-2020	0.034	2.082**	0.008	0.778	-0.005	-0.434	0.011	1.169
1900-1940	0.014	2.414**	0.011	2.443**	0.014	2.462**	0.009	1.924*
1941-1974	0.012	2.734***	-0.001	-0.223	-0.011	-3.091***	0.002	0.244
1900-1920	0.012	1.120	0.007	1.459	0.012	2.247**	0.011	2.117**
1921-1940	0.016	3.547***	0.016	1.990**	0.016	1.572	0.007	0.863
1941-1960	0.013	2.067**	-0.009	-1.181	-0.010	-2.240**	0.001	0.192
1961-1974	0.011	1.717*	0.009	0.720	-0.012	-2.057**	0.002	0.147
1978-2000	0.050	1.697*	0.014	0.791	-0.006	-0.334	0.004	0.272
2001-2020	0.017	1.762*	0.002	0.178	-0.004	-0.284	0.018	2.451**
1989-2010	0.017	1.578	0.014	1.136	0.002	0.187	0.009	0.851

Sample Period	May		June		July		August	
	beta	**t-stat**	**beta**	**t-stat**	**Beta**	**t-stat**	**beta**	**t-stat**
1900-2020	-0.003	-0.877	**-0.012**	**-3.219*** **	**-0.016**	**-4.371*** **	-0.001	-0.213
1900-1974	-0.003	-0.732	-0.010	-2.358**	-0.018	-4.978	0.002	0.568
1978-2020	-0.004	-0.494	-0.016	-2.090**	-0.012	-1.514	-0.006	-0.665
1900-1940	-0.006	-1.165	-0.007	-1.120	-0.018	-3.527***	-0.001	-0.123
1941-1974	0.001	0.105	-0.013	-2.471**	-0.017	-3.569***	0.005	1.245
1900-1920	0.000	-0.041	0.004	0.588	-0.019	-2.703***	-0.008	-1.160
1921-1940	-0.012	-1.890*	-0.017	-1.771*	-0.018	-2.322**	0.007	0.799
1941-1960	-0.005	-0.481	-0.011	-1.799*	-0.025	-3.943***	0.005	0.954
1961-1974	0.010	1.544	-0.016	-1.726*	-0.016	-1.744*	0.000	0.016
1978-2000	-0.010	-0.872	-0.016	-1.430	-0.009	-0.712	0.001	0.084
2001-2020	0.003	0.292	-0.014	-1.625	-0.015	-1.763*	-0.013	-1.503
1989-2010	-0.004	-0.404	-0.018	-1.828*	-0.003	-0.292	-0.009	-0.922

Sample Period	September		October		November		December	
	beta	**t-stat**	**beta**	**t-stat**	**Beta**	**t-stat**	**beta**	**t-stat**
1900-2020	**0.010**	**1.977*** **	-0.004	-0.676	-0.006	-1.048	-0.004	-0.888
1900-1974	0.011	3.027***	-0.007	-1.487	0.002	0.474	-0.005	-1.204
1978-2020	0.010	0.749	0.001	0.099	-0.019	-1.525	-0.004	-0.329
1900-1940	0.009	1.721*	-0.015	-2.696***	-0.002	-0.402	-0.007	-1.511
1941-1974	0.013	2.735***	0.004	0.662	0.007	1.378	-0.002	-0.285
1900-1920	0.003	0.453	-0.008	-1.072	-0.009	-1.186	-0.004	-0.985
1921-1940	0.016	1.820*	-0.023	-2.794***	0.004	0.408	-0.010	-1.210
1941-1960	0.025	4.306***	0.007	0.799	0.014	2.028**	-0.005	-0.710
1961-1974	0.005	0.472	0.010	0.447	-0.012	-1.363	0.014	0.736
1978-2000	0.022	0.984	0.002	0.100	-0.038	-1.778	-0.014	-0.682
2001-2020	**-0.004**	**-0.459**	0.000	0.024	0.003	0.373	0.008	1.086
1989-2010	**-0.005**	**-0.357**	-0.008	-0.588	-0.002	-0.181	0.006	0.868

Notes: Table 6 presents the coefficients estimates and the t-statistics of the regression in a form of $R_t = \alpha_0 + \beta_i D_{it} + e_t$, where R_t is the continuously compounded monthly returns, D_{it} is the dummy variable of the calendar month, α_0 is the constant and e_t is the error term. Newey-West (1987) heteroskedasticity and autocorrelation adjusted standard errors are used to calculate p-values as reported next to the coefficients. ***: significant at the 1 percent level; **: significant at the 5 percent level; *: significant at the 10 percent level. The values highlighted in **bold** are related with relevant information. **Source:** Own elaboration.

From the regressions, a number of points are evident. Over the entire sample period, the coefficients on the months of January, February, April and September are positive, and for the months of January (0.021), September (0.010) and April (0.008) are statistically significant at 1%, 5% and 10% level respectively. Despite that, none of these seasonal patterns is statistically significant at the conventional levels over all the subperiods under scrutiny.

Still, the evidence for the January anomaly suggests that this pattern is strong over several subsamples and there is a higher mean return in January when comparing with the remaining months. The only subsample which generates an insignificant positive coefficient is in 1900-1920 subperiod. Curiously, the January effect does not exist in the 1989-2010 subperiod which is in line with the conclusions obtained in similar Portuguese calendar anomalies studies (Balbina and Martins, 2002; Fountas and Segredakis, 2002; Darrat et al., 2011; Lobão and Lobo, 2018).

When examining the September coefficients, it seems that the effect was particularly strong in the first 74 years of the sample being that only a smaller subperiod, 1900-1920, does not attain statistical significance. Since 1978, we can observe that the strength of the t-statistic vanishes. Moreover, only the recent subperiod, i.e. 2001-2020 and 1989-2010 indicate negative coefficients. The negative outcome in 1989-2010 subperiod is in line with Silva (2010) study, and at a more comprehensive level, Siegel (2014). However, we cannot conclude that the September effect is present in the Portuguese stock market.

The evidence shows a poor return performance in July (-0.016) and June (-0.012). However, our conclusion strongly depends on which subperiod we are conducting our analysis. Over the full sample and on the 1900-1974, 1941-1974 and 1978-2020 subperiods, the June effect is strong. Nonetheless, as the sample size reduces, the statistical evidence diminishes and on recent periods, 1978-2000 and 2001-2020, the coefficients are no longer significant. Once again, reviewing the 1989-2010 subperiod, our results corroborate Fountas and Segredakis (2002), Silva (2010) and Lobão and Lobo (2018) papers.

At the beginning of the sample, the coefficients for July were predominantly significant at 1% level, although this statistical strength also appears to be decreasing with time because the t-statistics for the periods 1961-1974 and 1978-2000 are not statistically significant. Still, the 2001-2020 subperiod is significant at the 10% conventional level. Please note that if we have only examined the 1989-2010 subperiod, we would reach the same conclusions from previous Portuguese studies, i.e., there is no particular calendar pattern in July. In addition, the results would suggest that June is the worst month on the Portuguese stock market

Concerning the remaining months, April coefficients and t-statistics are generally positive, i.e., the mean returns in April are higher than the average return in the remaining months. However, besides the full sample, only the 1900-1940, 1900-1920 and 2001-2020 subperiods are statistically significant. In February, we have the 1941-1974 and 1941-1960 subperiods with negative coefficients and 1900-1940 and 1921-1940 subperiods with positive statistical significance. The fluctuation of the coefficients over the sample is also observed in March, May, August, October, November and December. In August and December we do not perceive any statistical significant subperiod. For May, only the 1921-1940 subperiod generates a significant and negative coefficient.

Table 7 displays the Halloween effect results. Our findings detect that the "*Sell in and May and Go away*" anomaly is present in the Portuguese stock market nowadays and is also observable in the full sample and on shorter subperiods until around 1940. After checking the monthly results, this outcome is not surprising given that returns are specially negative in June and July (summer months) and positive during the months of January and April (winter Months). As well, during the statistical descriptive analysis, we have identified higher average returns during winter months. Even so, there is no consistency in the evidence throughout the different samples.

To sum up, the presence of the Halloween effect supports Zhang and Jacobsen (2021) paper which also detects this anomaly in the Portuguese stock market. Nonetheless, it will be necessary to proceed with a deeper analysis in order to obtain more reasonable and rigorous insights, and in particular to investigate if there is a possibility to explore this anomaly. This analysis will be carried out in the following sections.

TABLE 7 – HALLOWEEN EFFECT: OLS REGRESSIONS

Sample Period	Halloween effect beta	t-stat
1900-2020	**0.008**	**2.070****
1900-1974	**0.007**	**2.752*****
1978-2020	0.008	0.887
1900-1940	**0.012**	**3.263*****
1941-1974	0.002	0.525
1900-1920	**0.009**	**2.088****
1921-1940	**0.015**	**2.480*****
1941-1960	0.002	0.340
1961-1974	0.003	0.398
1978-2000	0.003	0.196
2001-2020	**0.014**	**1.997****
1989-2010	**0.014**	**1.692***

Notes: Table 7 presents the coefficients estimates and the t-statistics of the regression in a form of $R_t = \alpha_0 + \beta_i D_{it} + e_t$, where R_t is the continuously compounded monthly returns, D_{it} is the dummy variable that equals 1 if the month falls on the period November through April and 0 otherwise and e_t is the error term. Newey-West (1987) heteroskedasticity and autocorrelation adjusted standard errors are used to calculate p-values as reported next to the coefficients. ***: significant at the 1 percent level; **: significant at the 5 percent level; *: significant at the 10 percent level. The values highlighted in **bold** are related with relevant information. **Source:** Own elaboration

Concerning Table 8, the first quarter stands from the others because it shows higher coefficients and also a higher number of statistically significant subperiods. This finding may be due to the higher performance of the returns on January and April. In the remaining quarters, the coefficients are mostly negative and the worst quarter is the last. In the fourth quarter, there is only statistically significant evidence in the 1900-1940, 1900-1920 and 1921-1940 subperiods.

TABLE 8 – QUARTER EFFECTS: OLS REGRESSIONS

Sample Period	1st quarter beta	t-stat	2nd quarter beta	t-stat	3rd quarter beta	t-stat	4th quarter beta	t-stat
1900-2020	0.011	3.216***	-0.003	-1.019	-0.002	-0.681	-0.006	-1.560
1900-1974	0.009	2.968***	-0.003	-0.981	-0.002	-0.704	-0.004	-1.388
1978-2020	0.015	1.853*	-0.003	-0.489	-0.003	-0.366	-0.009	-1.025
1900-1940	0.016	3.898***	-0.002	-0.415	-0.004	-0.912	-0.010	-3.015***
1941-1974	0.003	0.477	-0.004	-0.997	0.000	0.129	0.004	0.929
1900-1920	0.012	2.464**	0.006	1.125	-0.010	-1.613	-0.008	-2.008**
1921-1940	0.019	3.091***	-0.009	-1.452	0.002	0.242	-0.012	-2.141**
1941-1960	-0.002	-0.548	-0.006	-0.987	0.002	0.414	0.007	1.202
1961-1974	0.003	0.451	-0.002	-0.268	-0.002	-0.299	0.000	0.009
1978-2000	0.023	1.816*	-0.009	-0.806	0.006	0.411	-0.020	-1.444
2001-2020	0.006	0.704	0.003	0.391	-0.014	-1.908	0.005	0.582
1989-2010	0.013	1.456	-0.005	-0.671	-0.007	-0.767	-0.002	-0.211

Notes: Table 8 presents the coefficients estimates and the t-statistics of the regression in a form of $R_t = \alpha_0 + \beta_i D_{it} + e_t$, where R_t is the continuously compounded monthly returns, D_{it} is the dummy variable that equals 1 if month t falls in the first, second, third and fourth quarter of the year respectively and 0 otherwise. Newey-West (1987) heteroskedasticity and autocorrelation adjusted standard errors are used to calculate p-values as reported next to the coefficients. ***: significant at the 1 percent level; **: significant at the 5 percent level; *: significant at the 10 percent level. **Source:** Own elaboration

Table 9 reports the half-of-the-year estimates. Over the full sample, the coefficients are similar on the first and second half of the year. In the analysis of the different subperiods, the second half of the year has the most statistically significant coefficients. Similar to the disparity of the results observed in the Halloween effect, we are also unable to detect a consistent pattern in the half-of-the-year returns.

TABLE 9 – HALF-OF-THE-YEAR EFFECT: OLS REGRESSIONS

Sample Period	1st semester		2nd semester	
	beta	**t-stat**	**beta**	**t-stat**
1900-2020	0.006	2.142**	0.007	2.948***
1900-1974	0.004	1.529	0.007	3.455***
1978-2020	0.009	1.403	0.007	1.256
1900-1940	0.011	2.750***	0.003	0.969
1941-1974	-0.003	-0.805	0.012	4.427***
1900-1920	0.014	2.754***	0.0001	0.075
1921-1940	0.008	1.284	0.005	1.211
1941-1960	-0.006	-1.222	0.012	3.373***
1961-1974	0.001	0.184	0.012	3.026***
1978-2000	0.011	1.078	0.014	1.684*
2001-2020	0.007	0.979	0.979	-0.363
1989-2010	0.006	0.865	0.002	0.359

Notes: Table 9 presents the coefficients estimates and the t-statistics of the regression in a form of $R_t = \alpha_0 + \beta_i D_{it} + e_t$, where R_t is the continuously compounded monthly returns, D_{it} is the dummy variable that equals 1 if the corresponding return if month t falls on the second semester of the year and 0 otherwise. Newey-West (1987) heteroskedasticity and autocorrelation adjusted standard errors are used to calculate p-values as reported next to the coefficients. ***: significant at the 1 percent level; **: significant at the 5 percent level; *: significant at the 10 percent level.
Source: Own elaboration.

Table 10 displays the weekly OLS estimation results and Table 11 summarizes the main findings (highest and lowest coefficient, total number of positive and significant weekly coefficients, total number of negative and significant weekly coefficients). In the full sample, and also for the 1900-1974, 1900-1940 and 1900-1920 subperiods, the returns in the first week of the year are significantly positive and higher than the remaining weeks. The presence of a seasonal effect in the first week, which corresponds to the first trading days of January may be related with the turn-of-the-year effect (Roll, 1983; Lakonishok and Smidt, 1988). The turn-of-the-year (TOY) effect is characterized by high gains in the last trading day of December and in the first trading days of January. Further, this pattern is normally found in small stocks in comparison over high capitalization stocks.

In the remaining subperiods, week 1 effect does not persist. Still, we can also observe that the returns on week 53, corresponding to the last trading day in the month of December is statistically significant in the 1978-2020 subperiod. Once again, this finding may also be associated with the TOY effect.

We can also highlight the results obtained in the period 1978-2020 and 1978-2000 since week 43 is the worst week of the year which was also discovered in the Levy and Yagil (2012) study. This coefficient is not statistically significant at the conventional levels. Levy and Yagil (2012) suggest that the returns for week 43 are usually negative and for week 44 are normally positive. In our sample, in week 43, we have 60 years with negative returns and 57 years with positive returns. In week 44, we have 49 years with negative returns and 68 years with positive returns. Therefore, we cannot reach the same findings of Levy and Yagil (2012) paper.

The 1900-1940, 1921-1940 and 1941-1960 subperiods generate significant and negative coefficients in week 23. Since week 23 corresponds to the first week of June, this can provide further insights about the presence of a negative June effect.

Finally, Table 11 also demonstrates that (*i*) the 1961-1974 subperiod generated the highest coefficient in week 45 (0.060) and the smaller coefficient in week 48 (-0.046) (*ii*) the 1941-1960, 1921-1940 and 1900-1974 subperiods have the highest number of statistically significant coefficients; and (*iii*) the number of weeks with positive coefficients is greater than the number of weeks with negative coefficients for all subsamples, except for the 1941-1974 and 2001-2020 subperiods.

TABLE 10 – WEEKLY EFFECT: OLS REGRESSIONS

WN	*1900-2020*		*1900-1974*		*1978-2020*		*1900-1940*	
	beta	**t-stat**	**beta**	**t-stat**	**beta**	**t-stat**	**beta**	**t-stat**
1	0.024	3.571***	0.031	4.248***	0.011	0.841	0.037	3.389***
2	-0.007	-1.440	0.000	-0.001	-0.019	-2.301**	0.005	0.596
3	0.000	-0.039	-0.004	-0.950	0.006	0.801	-0.005	-0.665
4	-0.001	-0.255	-0.007	-1.364	0.010	1.516	-0.009	-0.980
5	0.004	1.611	0.007	1.995**	0.000	-0.060	0.008	1.300
6	0.004	1.126	0.006	1.242	0.000	0.073	0.009	1.187
7	-0.002	-0.320	-0.002	-0.222	-0.002	-0.382	0.002	0.153
8	-0.001	-0.444	-0.002	-0.506	0.000	-0.059	-0.003	-0.506
9	0.000	0.068	0.001	0.292	-0.001	-0.150	0.005	1.607
10	0.000	0.006	-0.002	-0.706	0.003	0.413	-0.001	-0.173
11	-0.002	-0.656	0.001	0.305	-0.007	-1.298	0.004	0.589
12	0.001	0.479	-0.002	-0.443	0.007	1.814*	-0.003	-0.397
13	0.007	1.858*	0.011	1.963**	0.001	0.259	0.018	1.902*
14	-0.003	-0.834	-0.008	-1.866*	0.004	0.508	-0.016	-2.275**
15	0.001	0.437	0.003	0.737	-0.001	-0.278	0.009	1.507
16	0.004	1.028	0.006	1.183	0.000	0.036	0.005	0.967
17	-0.005	-1.341	-0.007	-2.258**	-0.002	-0.187	-0.008	-1.927*
18	0.002	0.442	0.001	0.278	0.004	0.365	-0.001	-0.208
19	0.005	1.214	0.012	1.894*	-0.006	-1.156	0.014	1.418
20	-0.005	-1.698*	-0.008	-1.719*	-0.001	-0.359	-0.008	-1.119
21	-0.002	-0.970	-0.005	-1.408	0.002	0.621	-0.009	-2.054**
22	-0.003	-1.309	-0.003	-2.319**	-0.001	-0.241	-0.004	-1.796*
23	-0.011	-1.801*	-0.016	-1.908*	-0.003	-0.333	-0.016	-1.372
24	0.004	0.488	0.015	1.303	-0.013	-0.930	0.022	1.675*
25	-0.002	-0.314	-0.004	-0.429	0.001	0.072	-0.011	-1.058
26	-0.014	-2.406**	-0.016	-2.034**	-0.012	-1.290	-0.008	-0.705
27	0.008	1.425	0.010	1.323	0.003	0.537	0.006	0.575
28	-0.006	-1.850*	-0.010	-2.358**	0.001	0.304	-0.010	-2.242**
29	-0.001	-0.539	-0.001	-0.875	-0.001	-0.158	0.001	0.660
30	-0.003	-2.220**	-0.001	-0.920	-0.005	-2.410**	0.000	-0.149
31	-0.001	-0.709	0.000	0.209	-0.004	-0.974	0.001	0.687
32	0.001	0.271	0.002	0.439	-0.001	-0.194	-0.001	-0.153
33	0.001	0.248	0.001	0.159	0.002	0.210	-0.004	-0.787
34	0.000	-0.031	-0.002	-0.568	0.003	0.761	-0.003	-0.791
35	0.004	1.356	0.004	0.948	0.005	1.067	0.007	0.992
36	0.005	1.680*	0.007	1.724*	0.001	0.371	0.007	1.075
37	0.000	0.200	0.002	0.649	-0.002	-0.401	0.001	0.132
38	0.002	1.083	0.003	1.800*	0.001	0.270	0.003	1.374
39	-0.001	-0.255	-0.004	-1.171	0.005	0.859	-0.007	-1.174
40	-0.002	-0.585	-0.006	-1.388	0.004	0.479	-0.008	-1.253
41	0.012	1.971**	0.017	1.909*	0.005	0.631	0.007	0.560
42	-0.006	-0.831	-0.013	-1.745*	0.006	0.491	-0.003	-0.298
43	-0.010	-1.241	-0.002	-0.442	-0.025	-1.170	-0.011	-2.265**
44	0.002	0.343	0.003	0.562	-0.002	-0.264	0.004	0.913
45	0.000	-0.084	0.005	0.697	-0.009	-1.459	-0.005	-0.813
46	-0.002	-0.613	-0.004	-0.706	0.000	0.057	0.003	0.464
47	0.000	0.022	0.001	0.382	-0.002	-0.865	0.001	0.182
48	-0.012	-2.378**	-0.020	-2.736***	0.002	0.409	-0.016	-2.575**
49	0.007	1.174	0.018	2.242**	-0.012	-1.621	0.019	1.489
50	0.004	0.722	0.005	0.705	0.003	0.292	-0.007	-0.702
51	-0.014	-2.115**	-0.015	-2.348**	-0.010	-0.781	-0.015	-2.119**
52	-0.007	-0.947	-0.011	-1.393	0.000	-0.015	-0.006	-0.677
53	0.021	3.432***	0.005	1.294	0.049	3.397***	-0.001	-0.190

WN	*1941-1974*		*1900-1920*		*1921-1940*		*1941-1960*	
	beta	**t-stat**	**beta**	**t-stat**	**beta**	**t-stat**	**beta**	**t-stat**
1	0.024	2.601***	0.060	3.175	0.014	1.711*	0.028	2.364**
2	-0.007	-1.104	0.012	0.736	-0.001	-0.182	-0.001	-0.131
3	-0.003	-1.079	-0.014	-1.084	0.005	1.770*	-0.003	-0.992
4	-0.005	-1.355	-0.012	-0.696	-0.006	-1.013	-0.012	-2.052**
5	0.007	1.803*	0.006	0.682	0.010	1.188	0.008	1.410
6	0.002	0.411	0.014	1.320	0.004	0.358	0.002	0.381
7	-0.007	-1.838*	-0.009	-1.290	0.014	0.497	-0.009	-1.647*
8	0.000	-0.094	0.002	0.746	-0.008	-0.722	-0.003	-1.584
9	-0.005	-3.517***	0.005	0.999	0.005	1.584	-0.005	-2.454**
10	-0.003	-1.967**	-0.006	-0.730	0.005	1.216	0.000	-0.251
11	-0.002	-1.496	0.003	0.224	0.005	1.273	-0.002	-1.089
12	-0.001	-0.240	-0.006	-0.412	0.000	0.006	-0.003	-2.681***
13	0.002	0.586	0.028	1.545	0.008	1.895*	0.002	0.654
14	0.002	0.779	-0.016	-1.927	-0.015	-1.358	0.001	0.522
15	-0.005	-1.346	0.000	0.118	0.018	1.567	-0.006	-1.174
16	0.006	0.745	0.013	1.340	-0.003	-0.802	0.014	1.043
17	-0.006	-1.238	-0.005	-0.761	-0.010	-2.473**	-0.014	-2.199**
18	0.002	1.312	-0.003	-0.417	0.001	0.372	0.001	0.530
19	0.008	1.419	0.017	1.289	0.011	0.726	0.014	1.456
20	-0.007	-1.702*	-0.011	-1.582	-0.006	-0.445	-0.012	-1.835*
21	0.001	0.164	-0.006	-1.242	-0.012	-1.641	0.002	0.258
22	-0.002	-1.557	-0.001	-0.235	-0.008	-2.218**	-0.002	-0.853
23	-0.017	-1.335	-0.006	-0.283	-0.027	-2.586***	-0.034	-2.355**
24	0.005	0.257	0.011	0.637	0.035	1.675*	0.028	1.752*
25	0.006	0.417	-0.006	-0.323	-0.017	-1.645	-0.005	-0.416
26	-0.025	-2.683***	-0.008	-0.346	-0.009	-1.922*	-0.026	-2.458**
27	0.016	1.314	0.016	0.824	-0.005	-1.408	0.025	1.275
28	-0.009	-1.215	-0.016	-2.010	-0.004	-1.095	-0.018	-1.824*
29	-0.004	-1.829*	-0.002	-0.956	0.005	1.977**	-0.006	-1.901*
30	-0.003	-1.301	-0.002	-0.532	0.001	0.409	-0.003	-1.111
31	-0.001	-0.375	-0.003	-1.778	0.005	1.651*	0.000	-0.085
32	0.005	0.567	-0.002	-0.268	0.001	0.209	-0.003	-0.485
33	0.007	0.509	-0.004	-0.508	-0.003	-0.689	0.018	1.768*
34	0.000	-0.067	0.000	0.036	-0.007	-0.922	0.000	0.016
35	0.001	0.147	-0.005	-0.712	0.020	1.675*	0.001	0.210
36	0.006	3.363***	0.014	1.342	0.000	-0.039	0.008	3.199***
37	0.003	2.181**	-0.004	-0.448	0.005	1.752*	0.005	3.020***
38	0.003	1.155	0.002	0.935	0.004	1.063	0.009	2.933***
39	-0.001	-0.228	-0.004	-0.360	-0.011	-1.604	-0.001	-0.171
40	-0.003	-0.612	0.005	0.493	-0.023	-3.017***	-0.005	-0.666
41	0.029	2.440**	-0.021	-1.708	0.036	1.810*	0.031	1.942*
42	-0.025	-2.371**	0.010	0.765	-0.017	-1.222	-0.023	-2.348**
43	0.008	0.991	-0.007	-1.754	-0.014	-1.678*	0.002	0.620
44	0.002	0.200	-0.002	-0.876	0.010	1.146	0.020	2.073**
45	0.016	1.283	0.005	0.715	-0.015	-1.600	-0.012	-2.137**
46	-0.013	-1.524	-0.009	-1.170	0.016	1.294	0.003	1.063
47	0.002	0.629	0.005	0.759	-0.003	-0.266	0.000	-0.124
48	-0.026	-1.756*	-0.013	-1.536	-0.019	-2.116**	-0.013	-1.495
49	0.017	1.989**	0.017	0.931	0.022	1.176	0.013	1.266
50	0.019	1.957*	-0.001	-0.066	-0.012	-1.326	0.009	0.852
51	-0.016	-1.356	-0.014	-1.195	-0.016	-2.052**	-0.008	-0.553
52	-0.018	-1.241	-0.019	-1.179	0.008	2.082**	-0.021	-1.059
53	0.013	2.300**	-0.008	-0.824	0.006	0.983	0.008	1.699*

WN	1961-1974		1978-2000		2001-2020	
	beta	t-stat	beta	t-stat	beta	t-stat
1	0.020	1.279	0.022	1.483	-0.001	-0.064
2	-0.015	-1.561	-0.017	-1.355	-0.021	-2.035**
3	-0.002	-0.484	0.020	1.643	-0.009	-1.244
4	0.004	1.544	0.016	1.410	0.003	0.614
5	0.005	1.160	-0.001	-0.162	0.001	0.232
6	0.001	0.169	-0.001	-0.154	0.002	0.414
7	-0.004	-0.848	-0.007	-1.089	0.004	0.877
8	0.003	0.618	0.007	1.152	-0.009	-2.064**
9	-0.005	-2.684***	-0.004	-0.561	0.003	0.759
10	-0.007	-2.815***	0.010	0.846	-0.005	-0.560
11	-0.003	-1.025	-0.009	-1.266	-0.005	-0.562
12	0.003	0.499	0.008	1.293	0.007	1.286
13	0.002	0.290	-0.002	-0.289	0.006	1.380
14	0.003	0.589	0.000	0.000	0.009	2.490**
15	-0.003	-0.692	-0.007	-0.932	0.006	2.154**
16	-0.005	-0.732	0.000	-0.043	0.001	0.143
17	0.007	1.730*	0.007	0.615	-0.012	-0.985
18	0.004	1.466	-0.006	-0.416	0.015	1.333
19	0.000	0.033	-0.012	-1.573	0.002	0.317
20	0.000	0.214	0.003	0.755	-0.007	-1.124
21	-0.001	-0.439	0.004	0.839	0.000	-0.093
22	-0.003	-1.401	0.000	0.057	-0.003	-0.381
23	0.011	0.533	-0.001	-0.080	-0.005	-1.005
24	-0.031	-0.801	-0.020	-0.758	-0.006	-1.098
25	0.023	0.832	0.004	0.248	-0.004	-0.841
26	-0.023	-1.368	-0.015	-0.929	-0.008	-1.344
27	0.002	0.478	0.009	0.899	-0.004	-0.651
28	0.006	0.842	0.002	0.372	0.000	0.057
29	-0.001	-0.383	-0.002	-0.280	0.001	0.174
30	-0.003	-0.711	-0.006	-2.117**	-0.005	-1.343
31	-0.002	-0.520	0.000	0.070	-0.008	-1.320
32	0.016	0.839	-0.002	-0.358	0.001	0.091
33	-0.011	-0.384	0.007	0.656	-0.005	-0.565
34	-0.001	-0.117	0.005	0.813	0.001	0.172
35	0.000	0.048	0.005	0.664	0.004	1.079
36	0.002	1.281	0.005	1.027	-0.003	-0.525
37	-0.001	-0.371	0.002	0.373	-0.006	-1.250
38	-0.006	-2.166**	0.004	0.440	-0.001	-0.337
39	-0.001	-0.150	0.009	0.801	0.001	0.367
40	0.000	-0.010	0.007	0.543	0.001	0.069
41	0.025	1.486	0.004	0.264	0.007	1.205
42	-0.027	-1.239	0.016	0.676	-0.005	-0.973
43	0.018	0.880	-0.040	-1.017	-0.008	-1.485
44	-0.024	-0.919	-0.014	-1.320	0.012	2.296**
45	0.060	2.269**	-0.016	-1.515	-0.001	-0.192
46	-0.038	-1.888*	0.004	0.473	-0.004	-0.954
47	0.005	0.875	-0.003	-0.917	-0.001	-0.239
48	-0.046	-1.328	-0.001	-0.073	0.005	1.581
49	0.023	1.576	-0.024	-1.789*	0.001	0.205
50	0.035	1.916*	0.006	0.305	0.000	-0.041
51	-0.028	-1.515	-0.003	-0.130	-0.019	-1.212
52	-0.014	-0.652	-0.016	-0.700	0.018	0.979
53	0.022	1.757*	0.044	2.137**	0.054	2.766***

Notes: Table 10 presents the coefficients estimates (percentage) and the t-statistics of the regression in a form of $R_t = \alpha_0 + \beta_i D_{it} + e_t$, where R_t is the continuously compounded weekly returns, D_{it} is the dummy variable that equals 1, if the corresponding for week *i* is Week1 through Week 53 and 0 otherwise. Newey-West (1987) heteroskedasticity and autocorrelation adjusted standard errors are used to calculate p-values as reported next to the coefficients. ***: significant at the 1 percent level; **: significant at the 5 percent level; *: significant at the 10 percent level.
Source: Own elaboration

TABLE 11 – SUMMARY OF THE MAIN WEEKLY FINDINGS

	1900-2020		*1900-1974*		*1978-2020*		*1900-1940*	
	beta	**week**	**beta**	**week**	**beta**	**week**	**beta**	**week**
Maximum	0.024	1	0.031	1	0.049	53	0.037	1
Minimum	-0.014	26	-0.020	48	-0.025	43	-0.016	23
N. of Positive	25		26		27		24	
N. of Negative	28		27		26		29	
N. of Significant	12		18		4		11	
N. of Positive	5		8		2		3	
N. of Negative	7		10		2		8	

	1941-1974		*1900-1920*		*1921-1940*		*1941-1960*	
	beta	**week**	**beta**	**week**	**beta**	**week**	**beta**	**week**
Maximum	0.029	41	0.060	1	0.036	41	0.031	41
Minimum	-0.026	48	-0.021	41	-0.027	23	-0.034	23
N. of Positive	26		21		27		24	
N. of Negative	27		32		26		29	
N. of Significant	16		6		18		21	
N. of Positive	8		1		10		9	
N. of Negative	8		5		8		12	

	1961-1974		*1978-2000*		*2001-2020*	
	beta	**week**	**beta**	**week**	**beta**	**week**
Maximum	0.060	45	0.044	53	0.054	53
Minimum	-0.046	48	-0.040	43	-0.021	2
N. of Positive	26		27		25	
N. of Negative	27		26		28	
N. of Significant	8		3		6	
N. of Positive	4		1		4	
N. of Negative	4		2		2	

Notes: Table 11 exhibits the maximum, minimum, number of positive, negative and significant week coefficients for several subperiods. **Source:** Own elaboration.

5.2 Rolling Windows Regression Results

In Figure 1, we show the evolution of the β coefficients for the calendar months, and also the upper and lower bounds on its 95% confidence interval calculated based on Newey-West (1987) standard errors. Overall, betas fluctuate around zero and there are wide confidence bounds which diminishes the power of the results partially because of volatility.

In the case of January, the lower bound (in green) was above 0 practically from the beginning of the sample until 1980, and from 2000 until nowadays, which means that the betas were positive and statistically significant during these sub-periods. During the subperiod 1980-2000, in spite of the beta being positive and having a sudden growth, the results do not appear to be significant since the bands are above and below zero. The fact that the bands have widened in this period indicates that the high variability of returns reduced the statistical significance.

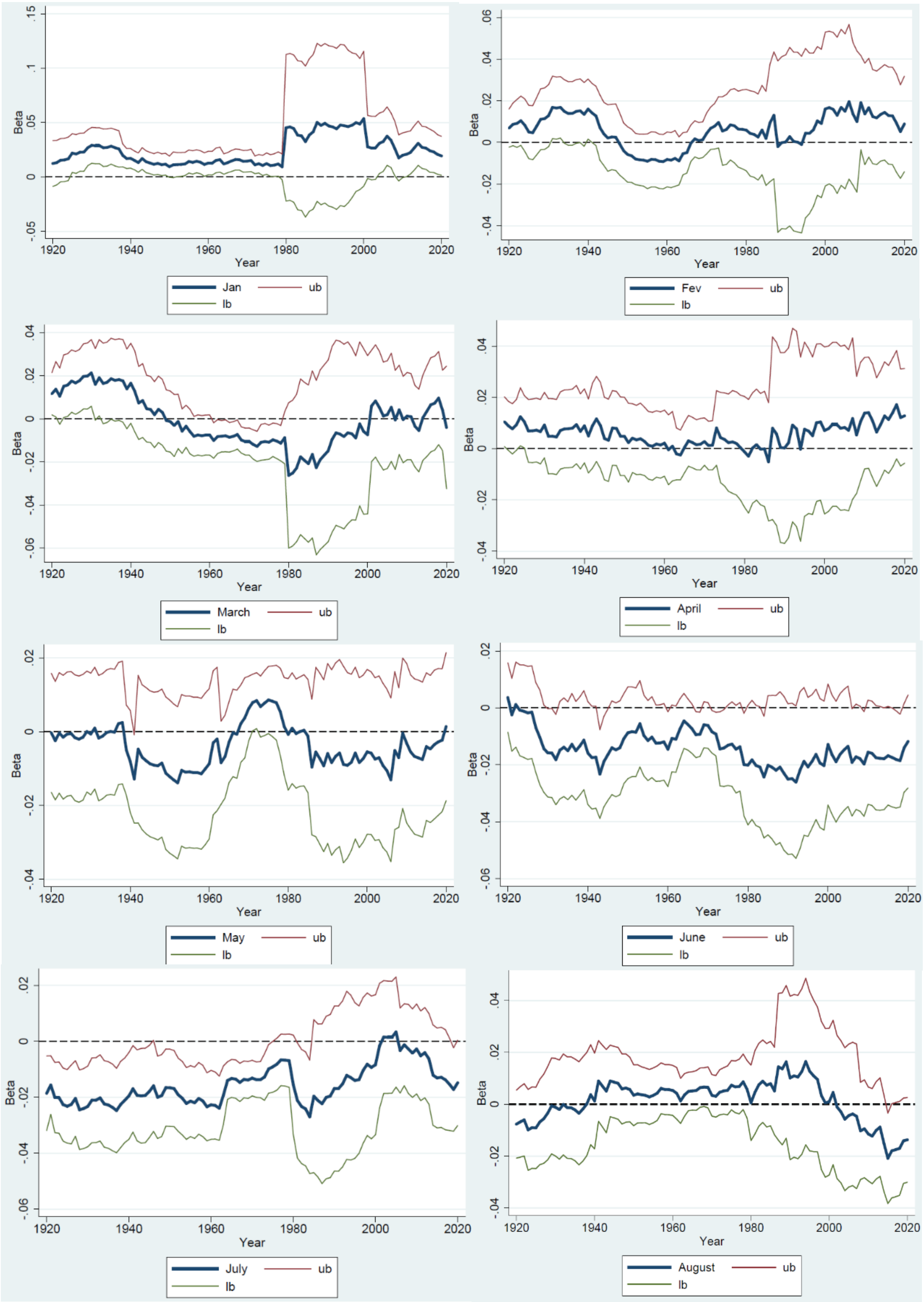
At the beginning of the sample, February also has a period with positive and significant coefficients and later on, the period 1940-1960 exhibits negative and insignificant coefficients. In March, we can highlight two trends. Initially, the returns in March are positive and higher than in the remaining months, but start to decrease and become negative around 1940, with a reversal of the observed calendar effect. In the 1940-1980 subperiod, there are still some years with significant coefficients. Later, there is an upward slopping trend but since 2000, progressively became very close to zero. In this case, as confidence intervals are broadened, there is no statistical significance. In April, coefficients have been constant and without major changes. Once again, as a result of the great variability of returns, there is no statistical evidence.

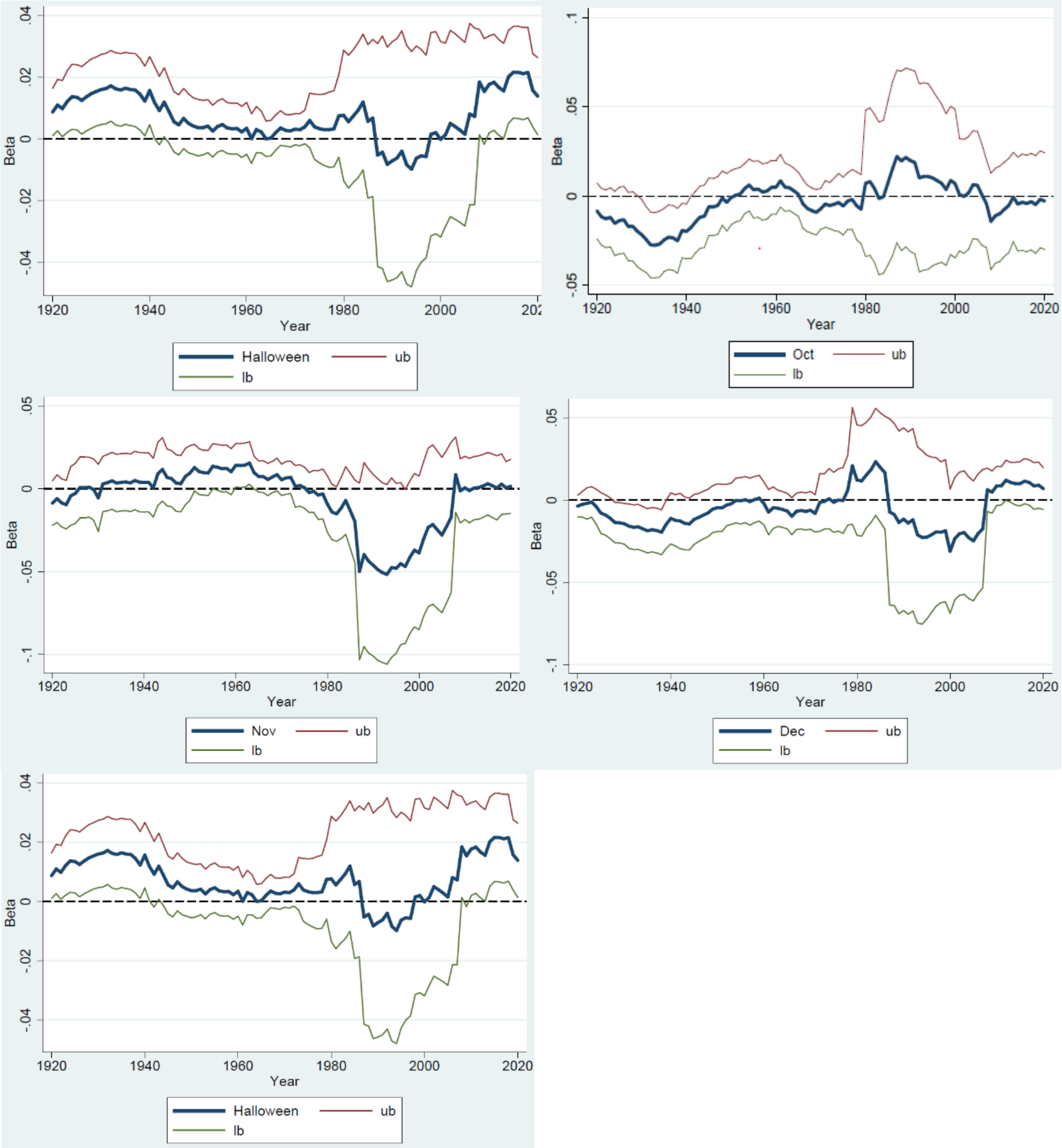
In May, coefficients are in general negative and insignificant. In June, betas are negative. For July, as the upper band has been below zero since the beginning of the sample until 1980, it indicates that in that period the returns in that month were significantly lower than in the other months. Since 1980, the statistical significance diminishes, or even ceases to exist. In August, coefficients are more or less around zero and since 2000 onwards these have been negative In September, betas have been specially positive in the 1980-2005 period. In October, betas have been negative with a downward trend until 1930 and then there is a shift. From 1950, coefficients are hovering around zero.

In November, results exhibit positive betas until 1980 but once again very close to zero and then these drastically decrease until 2000. In this case, there is no statistical significance. In recent years, betas are positive in December, and also were in the 1975-1985 period. In the remaining years, results reveal negative coefficients.

Concerning the Halloween effect, betas are positive with some exceptions on the 1985-1995 subperiod. Concerning the statistical evidence, since at the beginning of the sample (until around 1940) and at the end of the sample, both the upper and the lower bound are above 0, the returns are significant and superior when compared to the returns obtained in summer months.

FIGURE 1 - CALENDAR EFFECTS AND ROLLING WINDOWS REGRESSION RESULTS





Notes: 20-year rolling window OLS regressions of estimates for the 12 calendar month effects and the Halloween effect. The blue line is relative to the coefficient estimates of the effect, the red indicate the upper and the green line the lower 95% bounds calculated based on Newey-West (1987) standard errors. **Source:** Own elaboration.

5.3 Dynamic Analysis with OLS regression

For better understanding of the time-varying behaviour of the calendar anomalies and their persistence over time, we will examine how the annual t-statistics vary over time (e.g. Marquering et al, 2006) for the month of January, April, June, July, September and the Halloween effect since these are the most relevant detected calendar patterns.

Figure 2 exhibits a long time-series of annual January t-statistics where it is clear that t-statistics fluctuate around zero but the sign of the t-statistics changes over time with some periods generating a positive t-statistic, and even extremely high t-statistic (for instance 1916, 1951, 1962 and 1980). However, other periods generate a negative t-statistic. Thus, January effect seems to be weak statistically.

To analyse the impact of the discovery on seasonal patterns, we scrutinize the annual t-statistics around the period of discovery which was right after 1976, the year of the publication of Rozeff and Kinney (1976) paper. According with Figure 3, in the 1960-2000 subperiod, there is a downward OLS trend line but it is not clear if the research publication influence the t-statistics, notably because this also corresponds to a period of high instability.

Regarding the t-statistics series for the Halloween Effect, the t-statistics also fluctuate around zero but there is a slight downward slopping OLS trend line. According with the annual t-statistics, the Halloween anomaly is only present in some years. Figure 4 also demonstrates that right after 2002, the year of the publication of Bouman and Jacobsen (2002) study, the strength of the effect dropped. In 2002, the calendar effect was significant at 5% level since the annual t-statistic was 3.66. In the following year, the annual t-statistic was -1.097. These findings question the accuracy of our previous results obtained in the OLS regressions.

Figure 5 provides evidence from the April t-statistics. Once again, t-statistics fluctuate around zero. In the first years, signs are constantly changing and t-statistics seem to be moving in a descending trend. Since 1932, we identify an upward trend and there is several significant and positive annual t-statistics.

Figure 6 demonstrates that the July t-statistics are significantly negative until around 1960 which confirms our previous findings, but since 1960, t-statistics have been more on the positive side. Even tough, the fluctuations suggests that the July calendar pattern does not exist.

When analysing June t-statistics in Figure 7, we note that the signs of the t-statistics are constantly changing, switching from positive to negative in a fast pace. Still, in the recent years these move more or less randomly around zero which means that the June effect is also disappearing in the Portuguese market.

Figure 8 exhibit the evolution of the September t-statistics over time. The t-statistics have been mainly positive but not statistically significant.

To sum up, according with Marquering et al. (2006) research, the strength of the calendar effects are weakening and will eventually disappear in the long-run. Taken together with the results of the previous sections, this evidence of high instability of the calendar effects casts further doubt on the relevance and presence of the anomalies in the Portuguese stock market

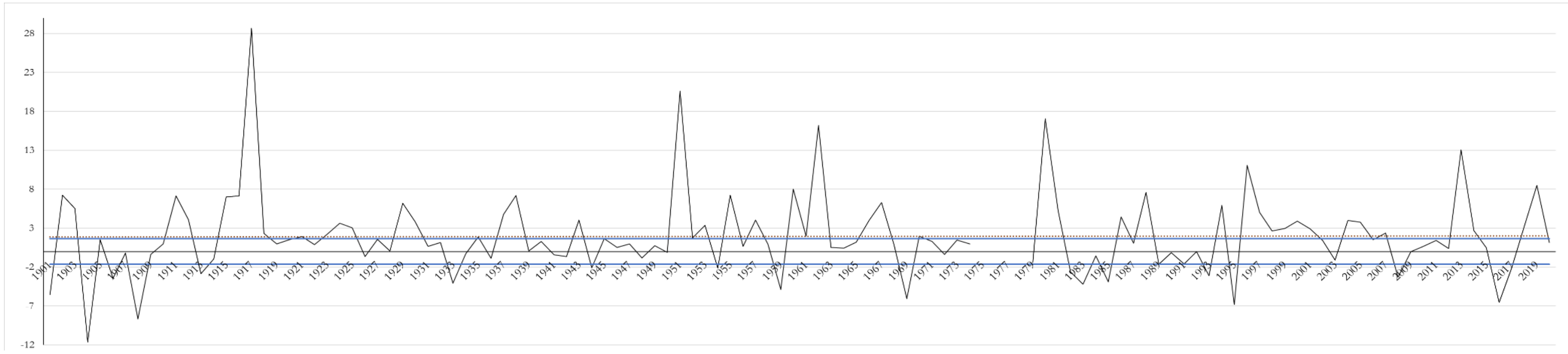


FIGURE 2 - JANUARY EFFECT

Notes: The blue and straight lines corresponds to the critical value of a two-sided test with a 90% confidence interval. The orange dashed line is the OLS trend line. **Source:** Own elaboration

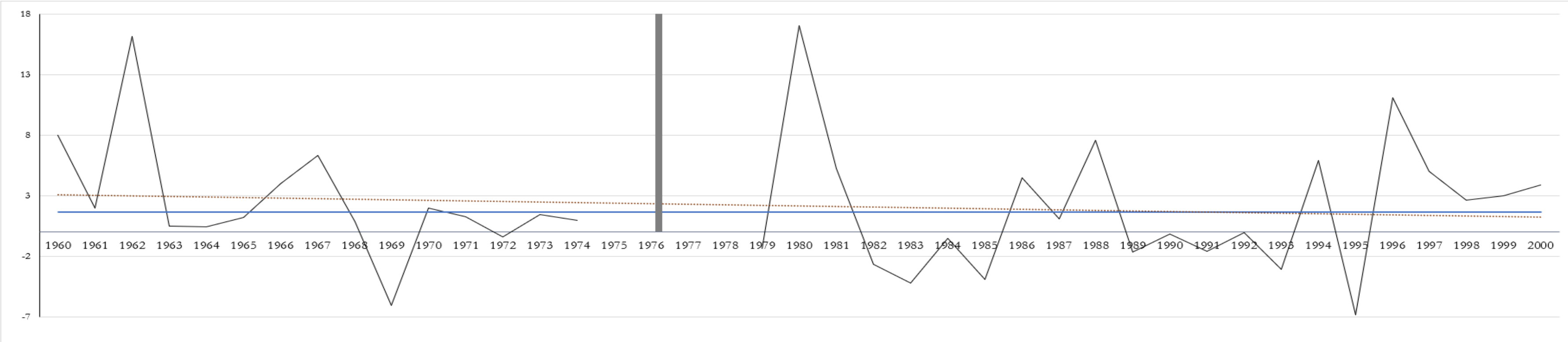


FIGURE 3 - JANUARY EFFECT AROUND THE FIRST YEAR OF PUBLICATION

Notes: The blue and straight lines corresponds to the critical value of a two-sided test with a 90% confidence interval. The orange dashed line is the OLS trend line. The vertical bar indicates the year of the first publication on the corresponding anomaly. **Source:** Own elaboration.

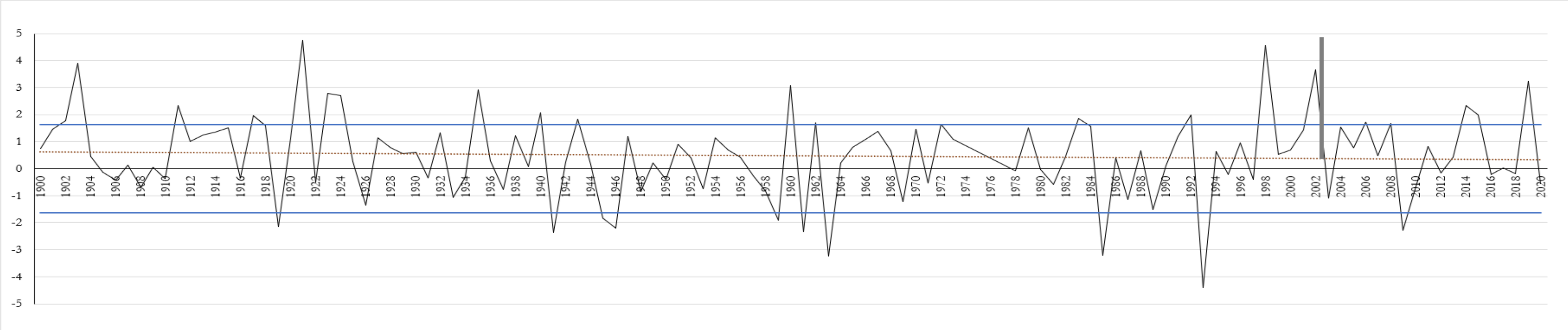


FIGURE 4 - HALLOWEEN EFFECT

Notes: The blue and straight lines corresponds to the critical value of a two-sided test with a 90% confidence interval. The orange dashed line is the OLS trend line. The vertical bar indicates the year of the first publication on the corresponding anomaly. **Source:** Own elaboration.

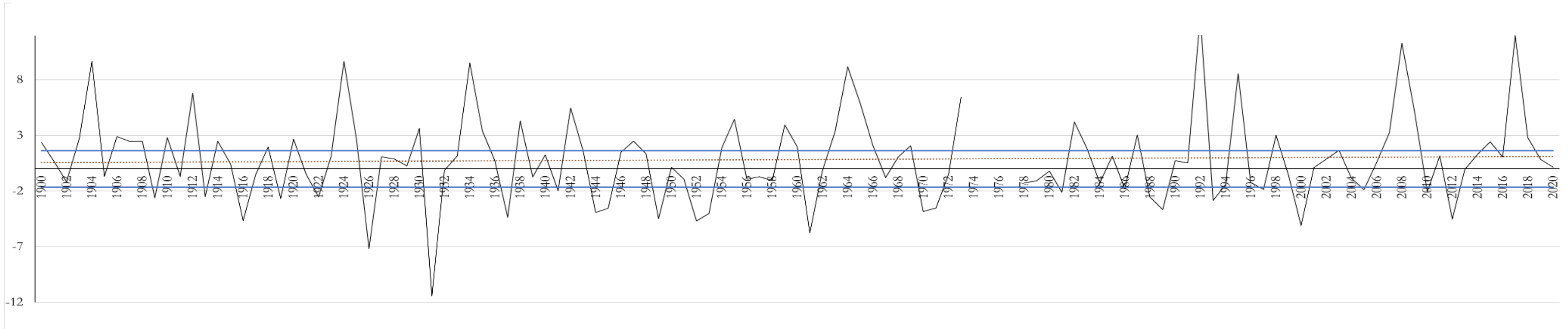


FIGURE 5 - APRIL EFFECT

Notes: The blue and straight lines corresponds to the critical value of a two-sided test with a 90% confidence interval. The orange dashed line is the OLS trend line. **Source:** Own elaboration.

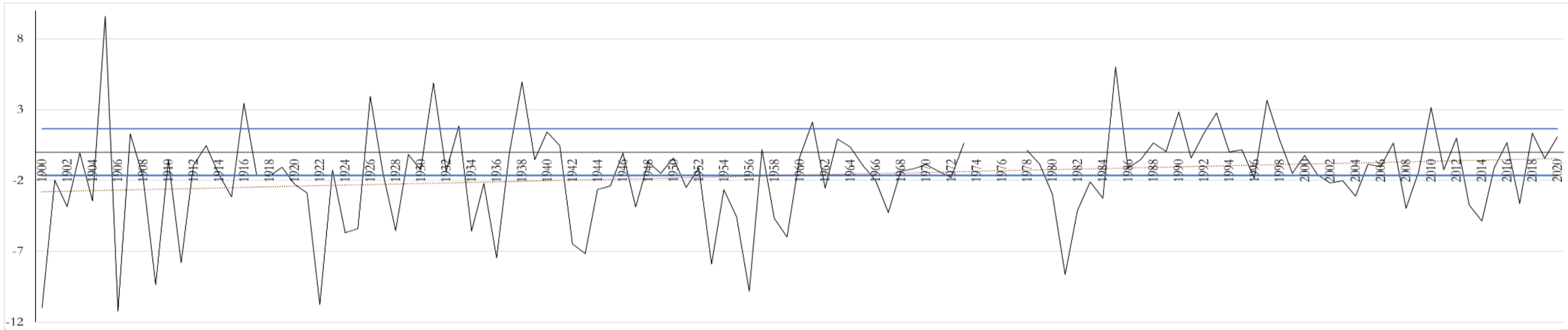


FIGURE 6 - JULY EFFECT

Notes: The blue and straight lines corresponds to the critical value of a two-sided test with a 90% confidence interval. The orange dashed line is the OLS trend line.

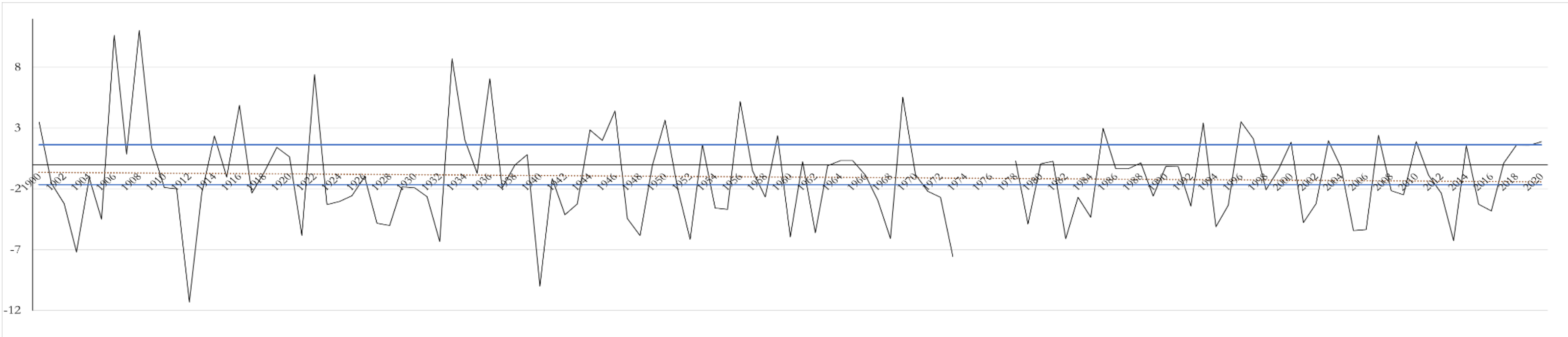


FIGURE 7 - JUNE EFFECT

Notes: The blue and straight lines corresponds to the critical value of a two-sided test with a 90% confidence interval. The orange dashed line is the OLS trend line.
Source: Own elaboration.

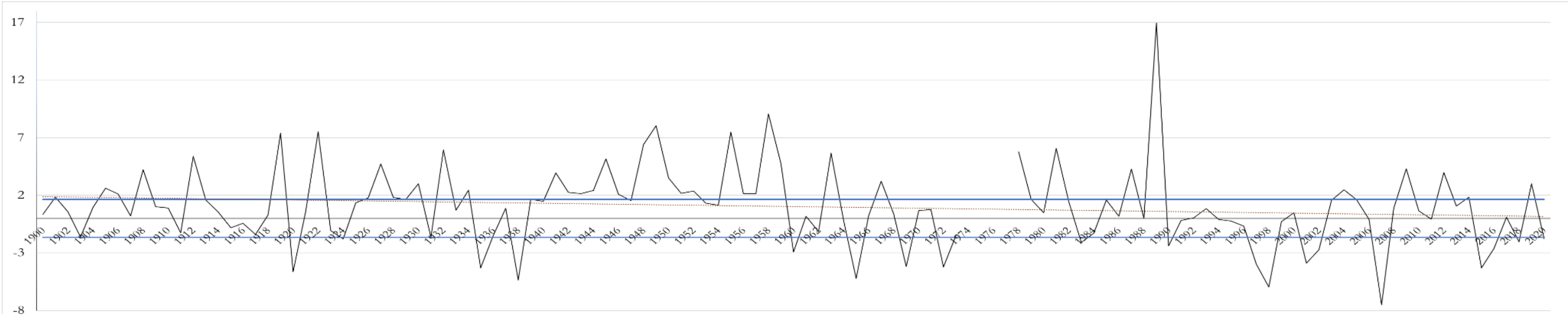


FIGURE 8 - SEPTEMBER EFFECT

Notes: The blue and straight lines corresponds to the critical value of a two-sided test with a 90% confidence interval. The orange dashed line is the OLS trend line.
Source: Own elaboration

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5.4 Robustness Checking

To check the strength of the previous results, we used as data the market risk premiums and replicated the previous OLS regressions with the Newey-West (1987) standard errors. When proceeding with the comparison of the monthly, Halloween, quarterly and semester empirical results from section 4.1 with the empirical evidence depict in Appendix B, we can infer that the results are practically the same which reinforces the robustness of the results previously found. Still, we have detected that there is no longer significant seasonality for April over the full sample and on the 1900-1974 subperiod. In addition, the strength of the coefficients in the second half of the year diminishes, i.e., the mean return difference of the second half of the year when comparing with the first half of the year is lower, and the statistical significance no longer exists for the full sample and the 1900-1974 subperiods.

The next step is to apply the GARCH (1,1) with t-student as an error distribution method, and the nonparametric Kruskal–Wallis test statistic. As this model required a continuous sample, we do not analyse the full sample period. Once again, to simplify the discussion of results, the regression findings are disclosed in Appendix C.

In the period 1900-1974, the highest coefficients are in January (0.010), March (0.010) and September (0.008). In contrast, the months with lower coefficients are in July (-0.012) and June (-0.006). In the 1978-2020 subperiod, the highest returns are in January and February and the lowest are in June and July.

Concerning the betas for January, when analysing longer subperiods, we perceive that the coefficients decreased but overall there is no significant impact in the statistical evidence, also confirmed by the K-W statistic. In February, the seasonality becomes statistically significant in the subsample which comprises the period between 1900 and 1974, yet, the Kruskal–Wallis statistic does not support this empirical result. In March, we find statistically significant betas in the 1900-1974 subsample. In contrast, the coefficients from the 1900-1940, 1900-1920 and 1941-1960 subsamples are no longer statistically significant. If we compare these results with the Kruskal-Wallis test, we do not reach to an accurate conclusion. In April, the coefficients are no longer statistically significant in the 1900-1974 period, and once again, differ from the non-parametric Kruskal-Wallis test. In June, both the coefficients and the Kruskal-Wallis statistic vary when comparing with evidence previously observed since some subperiods generate statistical significance results and others insignificance. For July, the coefficients are lower and the 1900-1974 subperiod turns to statistically significant. Similarly, the coefficients associated with the Halloween effect also decrease when comparing with the standard OLS empirical evidence. Contrary to the Kruskal-Wallis test results, the 1900-1974 subperiod no longer has statistical strength, but the 1978-2020 subperiod generates a significant t-statistic.

At last, the GARCH model was not applied to the weekly effect because there were some tests failures that invalidated the estimates. Therefore, when controlling the volatility of data via a different approach can influence results which is not in favour of the robustness of our results.

Appendix D exhibits the robust regression results. The full sample generates a positive but smaller coefficient for January, the coefficient for November turns negative and on the 1978-2020 subperiod, the Halloween effect is significant. The remaining differences are marginal and not as relevant.

5.5 Interaction between Calendar Effects

Table 12 examines the robustness of the Sell in May effect. After incorporating the January indicator, the Halloween effect is no longer statistical significant over the full sample and during the 1989-2010 subperiod. In contrast, the January coefficient is significant at the 10% conventional level. Further, in some periods the statistical significance of the Halloween effect vanishes. Therefore, the evidence suggests that the Halloween effect could be the January effect in disguise.

TABLE 12 – CONTROLLING THE IMPACT OF THE JANUARY EFFECT ON THE HALLOWEEN EFFECT

Sample Period	*Halloween effect* May-Oct	*Halloween effect* Nov-Apr	*Halloween effect controlled for the January effect* May-Oct	Nov-Apr	Jan
1900-2020	0.006	0.008	0.006	0.005	0.023
	(2.233**)	(2.070**)	(2.232**)	(1.195)	(3.423***)
1900-1974	0.005	0.007	0.005	0.006	0.016
	(2.665***)	(2.752***)	(2.663***)	(2.090**)	(3.782***)
1978-2020	0.007	0.008	0.007	0.002	0.036
	(1.150)	(0.887)	(1.149)	(0.269)	(2.050)
1900-1940	0.002	0.012	0.002	0.010	0.019
	(0.759)	(3.263***)	(0.759)	(2.848***)	(2.948***)
1941-1974	0.010	0.002	0.010	0.0001	0.012
	(3.228***)	(0.525)	(3.224***)	(0.035)	(2.305**)
1900-1920	0.003	0.009	0.003	0.007	0.016
	(0.867)	(2.088**)	(0.865)	(1.900*)	(1.375)
1921-1940	0.001	0.015	0.001	0.013	0.022
	(0.313)	(2.480***)	(0.312)	(2.128**)	(3.629***)
1941-1960	0.009	0.002	0.009	-0.001	0.012
	(2.032**)	(0.340)	(2.028**)	(-0.143)	(1.766*)
1961-1974	0.011	0.003	0.011	0.001	0.012
	(3.180***)	(0.398)	(3.170***)	(0.154)	(1.445)
1978-2000	0.018	0.003	0.018	-0.006	0.048
	(0.018)	(0.196)	(1.787*)	(-0.358)	(1.548)
2001-2020	-0.005	0.014	-0.005	0.012	0.023
	(-0.951)	(1.997**)	(-0.949)	(1.704*)	(2.070**)
1989-2010	-0.002	0.014	-0.002	0.012	0.023
	(-0.297)	(1.692)*	(-0.297)	(1.501)	(1.784*)

Notes: Table 12 exhibits the impact of the January effect on the Halloween effect over the full sample and on the different subperiods using OLS regressions with Newey-West (1987) standard errors. **Source:** Own elaboration.

5.6 Economic Significance

The presence of calendar effects indicate that the Portuguese stock market offers can offer an opportunity to earn abnormal gains. However, statistical significance may not imply economic impact. Jensen (1978) highlights the importance of trading profitability when assessing market efficiency. A simple way to see if seasonality patterns are exploitable is to compare investment trading rules. In a first step, we compare the Halloween strategy and January effect with the buy-and-hold strategy. In a second step, we implement a data-snooping resistant strategies simulation based on Hansen's (2005) "*Superior Predictive Ability*" test (or SPA test).

a) Simple Investing Strategies Simulation

The average returns and standard deviations are presented in Table 13 for index returns (a) and risk premiums (b) respectively.

TABLE 13 – BUY-AND-HOLD STRATEGY VS HALLOWEEN AND JANUARY STRATEGIES

(a) Stock returns

Sample Period	B&H		Halloween		January		Diff B&H Hal	Diff B&H Jan
	Return	**Std Dev**	**Return**	**Std Dev**	**Return**	**Std Dev**		
1900-1974	0.009	0.016	0.008	0.010	0.005	0.003	0.001	0.004
1978-2020	0.009	0.029	0.009	0.016	0.008	0.010	0.000	0.001
1900-1940	0.007	0.015	0.009	0.010	0.006	0.003	-0.002	0.001
1941-1974	0.011	0.017	0.008	0.010	0.004	0.002	0.003	0.007
1900-1920	0.007	0.012	0.008	0.008	0.006	0.004	-0.001	0.001
1921-1940	0.008	0.019	0.010	0.011	0.007	0.002	-0.002	0.001
1941-1960	0.009	0.018	0.006	0.009	0.004	0.002	0.003	0.005
1961-1974	0.014	0.016	0.010	0.012	0.005	0.002	0.004	0.010
1978-2000	0.016	0.033	0.013	0.019	0.014	0.010	0.003	0.002
2001-2020	0.001	0.021	0.004	0.010	0.001	0.004	-0.003	-0.001

(b) Risk premium

Sample Period	B&H		Halloween		January		Diff B&H Hal	Diff B&H Jan
	Return	**Std Dev**	**Return**	**Std Dev**	**Return**	**Std Dev**		
1900-1974	0.005	0.016	0.007	0.010	0.005	0.003	-0.001	0.000
1978-2020	0.003	0.028	0.006	0.015	0.008	0.010	-0.003	-0.004
1900-1940	0.002	0.015	0.007	0.010	0.006	0.003	-0.004	-0.003
1941-1974	0.009	0.017	0.006	0.010	0.004	0.002	0.002	0.005
1900-1920	0.002	0.012	0.005	0.008	0.005	0.004	-0.004	-0.003
1921-1940	0.003	0.019	0.008	0.011	0.006	0.002	-0.005	-0.004
1941-1960	0.007	0.018	0.005	0.009	0.004	0.002	0.002	0.003
1961-1974	0.012	0.016	0.009	0.011	0.004	0.002	0.003	0.008
1978-2000	0.006	0.033	0.009	0.019	0.013	0.010	-0.003	-0.007
2001-2020	0.0004	0.021	0.004	0.009	0.001	0.004	-0.003	-0.001

Notes: Table 13 compares average returns and standard deviation of the Buy-and-hold strategy, Halloween strategy and January strategy using stock returns (a) and risk premiums (b) over several subperiods.

From Table 13 (a), we observe that the Halloween strategy beats the buy-and-hold strategy over the 1900-1940, 1900-1920, 1921-1940 and 2001-2020 subsamples. According with Table 13 (b), in addition to the periods mentioned above, the "*Sell in May and Go Away*" strategy also outperforms the market in the 1900-1974, 1978-2000 and 1978-2020 subperiods. The magnitude in which the Halloween strategy is superior to the market cannot be considered substantial. As well, for all the sample periods examined, the risk of the Halloween strategy, measured by the standard deviation of the annual returns is smaller than for the buy-and-hold (B&H) strategy. In general, the Halloween strategy outperforms the buy-and-hold strategy approximately 50% of the years when considering stock returns. For risk premiums, the Halloween strategy surpasses the buy-and-hold benchmark approximately 57% of the years.

Table 13 also reveals the January strategy outcomes. For stock returns (a), January surpasses the B&H by only 0.1% in the last 20 years of the sample. For the risk premiums (b) analysis, the periods 1978-2020, 1900-1940, 1900-1920, 1921-1940, 1978-2000 and 2001-2020 outperform the B&H strategy with a slight margin. Likewise, the risk of the January strategy is also lower than the B&H strategy. In this scenario, the January strategy outperforms the market by a smaller percentage when comparing with the Halloween strategy. For stock returns, outperforms 43% of the times and for excess returns, 52% of the times.

A serious limitation of many studies on this topic is the neglection of the transaction costs which may significantly affect the behaviour of assets returns (e.g. Zhang and Jacobsen, 2013). Economic significance might disappear once transaction costs are taken into account. The implication is that no strategy based on anomalies could beat the market and there are no exploitable profit opportunities which gives credence to the EMH. Given that the return from the trading strategies is already low and not significant, the transaction costs would eliminate the potential profit opportunities.

b) "Superior Predictive Ability" Test

Table 14 exhibits in column (*1*), the lower, consistent and upper p-value of the SPA test for different subperiods. Appendix E contains a list of the documented models in this section. Results show that the p-values are statistically significant in the early years of the sample (1900-1974 at 5% level; 1900-1940 at 5% level; 1921-1940 at 10% level; 1900-1910 at 10% level). Therefore, the null hypothesis is rejected, i.e., there is statistical evidence that some strategies are better than the buy-and-hold benchmark in the periods mentioned above. Nonetheless, this outcome does not consider the impact of transaction costs which adversely influence the results. In the remaining subperiods, we have not found any model that provides an average return statistically higher than the one given by a buy-and-hold strategy.

TABLE 14 – SUPERIOR PREDICTIVE ABILITY TEST

Sample Period	SPA p-values (*1*)			Benchmark Model (*2*)
	L	**C**	**U**	**Loss Value**
1900-1974	0.020	0.044	0.063	-0.009
1978-2020	0.582	0.725	0.730	-0.011
1900-1940	0.023	0.033	0.036	-0.008
1941-1974	0.329	0.590	0.699	-0.011
1900-1920	0.287	0.366	0.375	-0.007
1921-1940	0.057	0.079	0.082	-0.009
1941-1960	0.142	0.239	0.282	-0.009
1961-1974	0.713	0.974	0.983	-0.013
1978-2000	0.615	0.796	0.799	-0.019
2001-2020	0.475	0.565	0.571	0.000
1900-1910	0.050	0.055	0.056	-0.003
1911-1920	0.505	0.525	0.353	0.011
1921-1930	0.117	0.160	0.168	-0.012
1931-1940	0.400	0.488	0.490	-0.005
1941-1950	0.376	0.542	0.581	-0.010
1951-1960	0.203	0.357	0.403	-0.008
2001-2010	0.586	0.657	0.659	-0.001
2011-2020	0.752	0.869	0.873	-0.002

Sample Period	Most significant Model (*3*)				Best Model (*4*)			
	Model Number	**Loss Value**	**t-stat**	**p-value**	**Model Number**	**Loss Value**	**t-stat**	**p-value**
1900-1974	609	-0.010	0.827	0.409	609	-0.010	0.827	0.409
1978-2020	1249	-0.013	0.504	0.614	1249	-0.013	0.504	0.614
1900-1940	2673	-0.011	1.441	0.150	3697	-0.011	1.457	0.146
1941-1974	101	-0.012	0.466	0.641	101	-0.012	0.466	0.641
1900-1920	3777	-0.010	1.042	0.298	3777	-0.010	1.042	0.298
1921-1940	2673	-0.014	1.510	0.132	2673	-0.014	1.510	0.132
1941-1960	103	-0.011	0.647	0.518	103	-0.011	0.647	0.518
1961-1974	37	-0.013	0.118	0.906	37	-0.013	0.118	0.906
1978-2000	3121	-0.022	0.399	0.690	3121	-0.022	0.399	0.690
2001-2020	997	-0.005	0.944	0.346	485	-0.005	0.931	0.353
1900-1910	1234	-0.009	2.089	0.038	1234	-0.009	1.688	0.093
1911-1920	2753	-0.014	0.671	0.503	2753	-0.014	0.671	0.503
1921-1930	2673	-0.019	1.343	0.181	2673	-0.019	1.343	0.181
1931-1940	2673	-0.008	0.727	0.468	2673	-0.008	0.727	0.468
1941-1950	119	-0.013	0.693	0.489	119	-0.013	0.693	0.489
1951-1960	613	-0.010	0.580	0.563	101	-0.010	0.571	0.568
2001-2010	1015	-0.006	1.116	0.266	503	-0.006	1.042	0.299
2011-2020	1509	-0.005	0.637	0.525	1253	-0.005	0.633	0.527

Notes: Table 14 reports SPA p-values: consistent p-value (column "C") of the SPA-test as well as lower (column "L") and upper bounds (column "U") for monthly stock-cash strategies that are compared to the buy-and-hold benchmark. Table also reports the sample loss for the buy-and-hold benchmark and the two-alternative stock-cash strategies that have the smallest sample loss value (*"best model"*) and the largest t-statistic (*"most significant"*) for the average relative performance ($\bar{d}_k$). These show the loss value, the corresponding t-statistic (of their sample loss relative to the benchmark), the "*p-values"* from the pairwise comparisons of "best" and "largest t-statistic" models with the benchmark. These p-values (unlike the SPA p-value) ignore the search over all models that preceded the selection of the model being compared to the benchmark, i.e., they do not account for the entire universe of models.

For the subperiods when the null hypothesis is rejected, we compare the Halloween (model 1009) and January (model 4094) investment strategies and infer that only in the 1900-1910 subperiod, a p-value of less than 10% was found for the strategy that follows the Halloween Effect (p-value= 0.082) . However, if we assume 25 basis points for turnover-dependent transaction costs, following Blitz and Van Vliet (2008) and Dichtl and Drobetz (2014) papers, the result found (p-value=0.154) is no longer significant at any conventional level

Columns (3) and (4) compare the alternative strategies in relation to the benchmark (column 2), namely the strategies that have the smallest sample loss value ("*best model*") and the largest t-statistic ("*most significant*") for the average relative performance. The simulation results reveal that the "*best model*" and the "*most significant model*" are usually the same.

Model 1234 is the only monthly stock-cash allocation strategy that has a statistically significant p-value in the 1900-1910 period. Nevertheless, these p-values ignore the search overall models that preceded the selection of the model being compared to the benchmark, i.e., they do not account for the entire universe of strategies. This strategy is based on the investment in the stock market in February, March, April, June, September, October, and December. In January, May, July and November, the investor should leave the stock market and, instead, invest in the cash market.

The benchmark model (model 0) is the buy-and-hold strategy. Model 4095 constantly invests in cash during all 12 months in each year of the sample.

Among the remaining strategies, we can also highlight model 2673 which consists on investing in the stock market during the months of January to April, as well as in August, September and November. Following the average returns analysis, this result is not surprising since the mean returns are higher in January, February, April and September, whereas, during July and October, returns were negative, as well as average returns are relatively low for May, June and December when compared to the mean return during the period of interest. Although model 2673 is the most significant and the best model in 1900-1940, 1921-1930 and 1931-1940, p-values are not statistically significant at any conventional level.

Summing up, these results corroborates the criticism of many backtest studies that perform their trading strategies on a single historical return path is that the outcome may be purely from chance, and not due to any genuine merit (Sullivan et al., 1999, 2001).

Although according to the OLS and Newey-West (1987) standard errors, the "*Sell in and May and Go away*" anomaly is present in the Portuguese Stock Market nowadays and is also observable in the full sample and on the shorter subperiods until around 1940, the SPA test results reveal that the Halloween effect never offered an opportunity for a statistically significant outperformance against the buy-and-hold benchmark. While our results challenges those reported in other recent studies that examine the Halloween effect as Zhang and Jacobsen (2013), they are also in line with Sullivan et al. (2001) paper negative findings for other calendar effects in stock returns. The same reasoning and conclusions are provided for the January strategy.

6. Conclusion

While a considerable body of empirical evidence has been collected on the impact of seasonal patterns in stock returns, the literature regarding the potential seasonality in Portuguese stock market is almost non-existent. This paper contributes to fill this gap since it provides evidence about the existence of several seasonal patterns in the Portuguese stock market with a sample covering the period 1900 to 2020. Moreover, is one of the few studies that analyses a longer sample and covers several methodologies in order to ensure the robustness of the empirical results.

The main findings were as follows. Initially, the main results on the full sample reveal the existence of a robust and positive January, September, April and Halloween effect. The worst months to invest in the market are July and June. The evidence for the January calendar pattern suggests that this pattern is particularly strong over several subsamples. Further, the Halloween effect is observable in shorter subperiods until around 1940.

Nowadays, a positive and significant January, April and Halloween seasonality is present in the market.. Moreover, there is a negative July effect. In general, these finds corroborate the literature, namely Fountas and Segredakis (2002), Silva (2010) and Lobão and Lobo (2018) Portuguese papers. Likewise, the Sell in May and Go Away effect is also observable in the Portuguese market according to Zhang and Jacobsen (2021) paper. For the quarters and semesters, the evidence is no longer clear given that the coefficients are constantly changing. Nevertheless, the first quarter stands out and is significant in some periods.

Regarding the week of the year effect, in the initial subperiods of the sample, we can highlight week 1 and week 53. As previously mentioned, this outcome may be related to the turn-of-the-year effect (Roll, 1983; Lakonishok and Smidt, 1988). The only finding that resembles the study by Levy and Yagil (2012) was detected in the period 1978-2020 and 1978-2000 since in these periods, week 43 is the worst week of the year. However, the coefficient is not statistically significant at the conventional levels.

Although the analysis of subperiods allows us to obtain a more detailed analysis of the performance of anomalies over time, it is important to consider other estimation methods, namely the rolling windows regressions. Through this methodology it was possible to detect that the sign of the effect changes over time with some periods generating positive t-statistics and other periods negative t-statistics which questions the presence of the potential patterns in the market. This result was also detected in the dynamic analysis of the yearly t-statistics. However, according to this methodology, the calendar effects do not exist in the market or are significantly weakening and vanishing.

To reinforce the power of our results, we have also applied OLS regressions with the Newey-West (1987) standard errors but using risk premiums, as well as the GARCH (1-1) with t-student standard errors and robust OLS regressions. All approaches led to some different findings when comparing with the traditional regression using total index returns. For instance, the January coefficient decreases, which means that although returns in January keep being significantly higher than the remaining months, the magnitude of the difference is smaller. This outcome casts doubts on the strength of the effect. Moreover, the impact of outliers is marginal. This outcome would be different if our analysis had considered the observation from January 1978.

Frequently, calendar anomalies are justified by the presence of a higher risk. However, this justification can only be feasible for returns in January. Also, the statistical evidence and the presence of the Halloween effect in the market can be justified by the high return in January.

Finally, we tested the economic significance of the investment strategies through 2 different methods: simple simulations and the SPA-test. Regarding the SPA-test, the Halloween and January effect cannot exceed the benchmark. Nevertheless, in some periods, there were some strategies that managed to beat the market. However, transaction costs were not considered.

Given the exhaustive analysis carried out, similarly to the study by Zhang and Jacobsen (2013), we find that the existence of calendar anomalies depends on the sample period and on the applied methodology. This result confirms the potential problems caused by intensive efforts of data mining, noise and selection bias. Likewise, alerts to the importance of studying the long time series and suggests that many if not all calendar month anomalies may be spurious.

There are some limitations in this study, namely the relatively lower dimension and liquidity of the market under analysis specially in the beginning of the sample. For further research, we suggest testing the impact of market conditions as there is a new trend in vogue which assumes that calendar effects can vary over time, associated with the Adaptive Market Hypothesis (Lo, 2004).

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Appendix A – Descriptive statistics

Sample Period	January				February			
	Mean	**(S.D.)**	**Skew.**	**Kurt.**	**Mean**	**(S.D.)**	**Skew.**	**Kurt.**
1900-2020	0.029	0.072	5.482	44.455	0.016	0.054	-0.378	6.667
1900-1974	0.021	0.034	1.276	5.656	0.014	0.036	0.035	2.042
1978-2020	0.043	0.111	3.952	20.643	0.019	0.076	-0.485	3.801
1900-1940	0.021	0.039	1.385	6.027	0.018	0.030	0.894	0.633
1941-1974	0.022	0.027	0.806	0.813	0.009	0.042	-0.176	1.952
1900-1920	0.018	0.051	1.484	4.089	0.013	0.022	0.485	1.323
1921-1940	0.024	0.021	-0.492	0.253	0.023	0.037	0.679	-0.478
1941-1960	0.021	0.028	1.261	1.434	0.001	0.032	0.139	0.844
1961-1974	0.023	0.027	0.185	0.992	0.021	0.051	-0.779	2.947
1978-2000	0.066	0.145	3.126	11.836	0.032	0.094	-0.855	3.316
2001-2020	0.017	0.042	-1.648	5.194	0.032	0.099	-0.836	2.946
1989-2010	0.021	0.052	-0.561	1.207	0.018	0.060	0.190	-0.928

Sample Period	March				April			
	Mean	**(S.D.)**	**Skew.**	**Kurt.**	**Mean**	**(S.D.)**	**Skew.**	**Kurt.**
1900-2020	0.010	0.048	-1.016	7.348	0.017	0.049	2.333	14.279
1900-1974	0.012	0.033	1.027	1.697	0.014	0.037	0.510	4.577
1978-2020	0.006	0.068	-1.161	4.260	0.021	0.065	2.577	11.713
1900-1940	0.020	0.037	0.617	0.913	0.016	0.030	-0.672	3.320
1941-1974	0.001	0.023	1.371	3.200	0.012	0.046	0.959	4.163
1900-1920	0.018	0.026	2.146	5.683	0.017	0.024	1.792	3.676
1921-1940	0.023	0.047	0.160	-0.314	0.015	0.035	-1.392	2.651
1941-1960	0.0001	0.020	0.683	0.449	0.011	0.036	1.996	7.350
1961-1974	0.002	0.028	1.703	4.239	0.015	0.058	0.489	2.899
1978-2000	0.014	0.070	-0.685	3.454	0.024	0.085	2.243	7.516
2001-2020	0.024	0.055	1.094	1.389	0.018	0.032	0.224	-0.087
1989-2010	0.007	0.046	0.894	1.818	0.014	0.048	0.121	0.958

Sample Period	May				June			
	Mean	**(S.D.)**	**Skew.**	**Kurt.**	**Mean**	**(S.D.)**	**Skew.**	**Kurt.**
1900-2020	0.007	0.044	1.485	5.071	-0.001	0.040	0.490	0.935
1900-1974	0.005	0.039	1.959	8.311	0.000	0.033	0.360	0.814
1978-2020	0.007	0.052	1.043	2.580	-0.003	0.050	0.606	0.444
1900-1940	0.002	0.035	1.830	7.222	0.002	0.037	0.555	0.522
1941-1974	0.010	0.044	1.985	8.869	-0.002	0.028	-0.386	0.672
1900-1920	0.007	0.040	2.452	8.403	0.010	0.026	0.781	-0.578
1921-1940	-0.003	0.030	0.074	1.097	-0.007	0.045	0.981	0.800
1941-1960	0.004	0.053	2.454	9.421	-0.001	0.028	-0.332	-0.575
1961-1974	0.022	0.022	-0.091	0.015	-0.002	0.030	-0.476	2.840
1978-2000	0.010	0.058	1.363	3.438	0.004	0.057	0.802	-0.260
2001-2020	0.004	0.046	0.236	-0.145	-0.012	0.040	-0.632	-0.192
1989-2010	0.001	0.048	0.424	-0.301	-0.011	0.047	-0.018	-0.727

Sample Period	July				August			
	Mean	**(S.D.)**	**Skew.**	**Kurt.**	**Mean**	**(S.D.)**	**Skew.**	**Kurt.**
1900-2020	-0.005	0.039	0.518	6.210	0.009	0.043	0.950	7.541
1900-1974	-0.007	0.029	-0.454	2.338	0.011	0.031	-0.626	3.171
1978-2020	0.000	0.052	0.566	4.372	0.006	0.058	1.382	5.716
1900-1940	-0.009	0.030	-0.156	1.458	0.007	0.036	-0.719	2.605
1941-1974	-0.005	0.027	-0.936	4.916	0.016	0.024	0.553	1.035
1900-1920	-0.010	0.030	-1.102	2.592	0.000	0.031	-1.487	9.709
1921-1940	-0.008	0.032	0.627	0.947	0.015	0.039	-0.639	0.082
1941-1960	-0.013	0.028	-1.484	4.728	0.014	0.023	0.874	2.872
1961-1974	0.008	0.021	1.376	3.483	0.018	0.027	0.210	-0.077
1978-2000	0.011	0.057	1.125	3.820	0.020	0.067	1.471	5.151
2001-2020	-0.013	0.042	-1.698	2.733	-0.011	0.042	-0.413	-0.674
1989-2010	0.003	0.043	-1.061	4.016	-0.003	0.047	0.012	-0.141

Sample Period	September				October			
	Mean	**(S.D.)**	**Skew.**	**Kurt.**	**Mean**	**(S.D.)**	**Skew.**	**Kurt.**
1900-2020	0.019	0.058	3.084	21.096	0.006	0.060	1.097	7.889
1900-1974	0.019	0.031	0.343	2.566	0.002	0.038	-0.297	0.824
1978-2020	0.020	0.087	2.53	10.812	0.012	0.087	0.903	3.835
1900-1940	0.016	0.035	0.284	2.443	-0.006	0.034	-1.009	1.006
1941-1974	0.023	0.025	0.977	1.918	0.012	0.040	-0.069	0.322
1900-1920	0.009	0.029	-1.241	7.885	-0.001	0.033	-2.060	5.480
1921-1940	0.023	0.04	0.623	0.138	-0.012	0.035	-0.204	-0.710
1941-1960	0.032	0.027	0.889	1.596	0.015	0.040	0.035	0.252
1961-1974	0.008	0.015	-0.215	-1.553	0.013	0.036	0.259	1.626
1978-2000	0.040	0.110	2.070	6.712	0.021	0.101	1.469	2.268
2001-2020	-0.003	0.044	-0.145	-0.734	-0.003	0.044	-0.145	-0.734
1989-2010	0.001	0.068	0.88	4.172	-0.002	0.066	-1.812	4.330

Sample Period	November				December			
	Mean	**(S.D.)**	**Skew.**	**Kurt.**	**Mean**	**(S.D.)**	**Skew.**	**Kurt.**
1900-2020	0.005	0.052	-3.346	24.057	0.006	0.053	-1.051	20.621
1900-1974	0.010	0.036	-0.688	2.29	0.006	0.033	1.009	4.369
1978-2020	-0.006	0.073	-3.088	16.385	0.008	0.076	-1.199	12.823
1900-1940	0.006	0.039	-0.927	2.56	0.002	0.028	-0.202	1.63
1941-1974	0.015	0.032	-0.015	0.881	0.011	0.039	1.364	4.171
1900-1920	-0.001	0.033	-2.158	6.77	0.004	0.015	-1.107	3.638
1921-1940	0.012	0.043	-0.654	1.178	-0.001	0.037	0.047	0.003
1941-1960	0.010	0.028	-0.277	0.901	0.005	0.028	1.005	1.313
1961-1974	0.022	0.030	0.554	0.736	0.015	0.051	1.328	3.976
1978-2000	-0.015	0.094	-2.595	10.537	0.007	0.101	-0.994	7.698
2001-2020	0.002	0.067	-2.16	5.774	0.004	0.036	0.139	-0.016
1989-2010	0.004	0.038	0.62	-0.101	0.010	0.031	1.195	2.115

Sample Period	Nov-Apr				May-Oct			
	Mean	**(S.D.)**	**Skew.**	**Kurt.**	**Mean**	**(S.D.)**	**Skew.**	**Kurt.**
1900-2020	0.014	0.056	1.527	31.011	0.006	0.049	1.699	12.849
1900-1974	0.013	0.035	0.472	3.302	0.005	0.034	0.408	3.358
1978-2020	0.015	0.080	1.310	18.697	0.007	0.066	1.697	8.733
1900-1940	0.014	0.034	0.274	3.211	0.002	0.035	0.209	2.166
1941-1974	0.012	0.035	0.702	3.567	0.010	0.033	0.788	5.404
1900-1920	0.011	0.031	1.049	8.877	0.003	0.032	-0.039	6.053
1921-1940	0.016	0.038	-0.223	0.671	0.001	0.039	0.367	0.146
1941-1960	0.010	0.030	0.955	2.483	0.009	0.037	0.986	5.577
1961-1974	0.014	0.042	0.447	3.232	0.011	0.027	0.067	1.692
1978-2000	0.021	0.102	1.165	12.346	0.018	0.078	1.930	6.751
2001-2020	0.008	0.043	-1.502	6.478	-0.005	0.047	-1.036	2.750

Sample Period	1st semester				2nd semester			
	Mean	**(S.D.)**	**Skew.**	**Kurt.**	**Mean**	**(S.D.)**	**Skew.**	**Kurt.**
1900-2020	0.013	0.053	2.738	31.488	0.007	0.052	0.438	17.030
1900-1974	0.011	0.036	0.854	3.868	0.007	0.034	-0.095	2.238
1978-2020	0.015	0.074	2.538	21.418	0.007	0.073	0.446	10.430
1900-1940	0.013	0.035	0.777	2.665	0.003	0.034	-0.394	1.861
1941-1974	0.009	0.036	0.965	5.415	0.012	0.032	0.459	2.503
1900-1920	0.014	0.032	1.848	6.837	0.000	0.029	-1.606	5.723
1921-1940	0.013	0.038	0.106	0.237	0.005	0.039	0.044	0.052
1941-1960	0.006	0.034	1.746	8.498	0.012	0.032	0.130	1.360
1961-1974	0.013	0.039	0.139	3.451	0.012	0.031	1.051	4.926
1978-2000	0.025	0.090	2.539	16.192	0.014	0.090	0.395	7.371
2001-2020	0.005	0.047	-1.199	4.288	-0.002	0.045	-1.324	4.002

Sample Period	1st quarter Mean	(S.D.)	Skew.	Kurt.	2nd quarter Mean	(S.D.)	Skew.	Kurt.
1900-2020	0.018	0.059	3.070	36.242	0.008	0.045	1.647	8.942
1900-1974	0.016	0.034	0.700	2.916	0.007	0.037	1.064	5.043
1978-2020	0.022	0.087	2.478	19.903	0.009	0.057	1.758	7.838
1900-1940	0.020	0.035	1.002	3.072	0.007	0.034	0.610	2.442
1941-1974	0.011	0.032	0.204	2.385	0.007	0.040	1.411	6.714
1900-1920	0.016	0.035	1.812	7.332	0.008	0.045	1.647	8.942
1921-1940	0.023	0.036	0.284	0.285	0.006	0.036	1.248	5.473
1941-1960	0.007	0.028	0.560	1.470	0.009	0.053	1.632	7.952
1961-1974	0.015	0.038	-0.179	2.807	0.012	0.041	0.425	4.530
1978-2000	0.037	0.108	2.375	14.336	0.013	0.067	1.918	6.681
2001-2020	0.006	0.052	-1.740	5.952	0.004	0.041	-0.167	0.165

Sample Period	3rd quarter Mean	(S.D.)	Skew.	Kurt.	4th quarter Mean	(S.D.)	Skew.	Kurt.
1900-2020	0.008	0.048	2.268	18.550	0.006	0.055	-0.786	15.632
1900-1974	0.008	0.032	-0.135	2.221	0.006	0.035	-0.055	2.265
1978-2020	0.009	0.068	2.278	12.123	0.005	0.078	-0.705	9.195
1900-1940	0.005	0.035	-0.091	1.814	0.000	0.034	-0.763	1.894
1941-1974	0.011	0.028	-0.030	2.907	0.014	0.035	0.659	2.002
1900-1920	0.008	0.048	2.268	18.550	0.001	0.028	-2.283	7.486
1921-1940	0.007	0.034	-0.131	1.943	0.005	0.034	-0.387	1.658
1941-1960	0.009	0.060	2.456	15.310	0.014	0.033	0.375	0.379
1961-1974	0.011	0.022	0.713	0.781	0.013	0.039	0.979	3.718
1978-2000	0.024	0.081	2.201	9.048	0.004	0.099	-0.492	6.042
2001-2020	-0.009	0.042	-0.665	0.327	0.005	0.046	-2.009	8.113

Sample Period	Annual Mean	(S.D.)	Skew.	Kurt.	Weeks Mean	(S.D.)	Skew.	Kurt.
1900-2020	0.010	0.052	1.622	24.623	0.002	0.049	-0.145	34.525
1900-1974	0.009	0.035	0.436	3.263	0.002	0.047	0.973	21.066
1978-2020	0.011	0.073	1.490	15.970	0.003	0.052	-1.571	49.329
1900-1940	0.008	0.035	0.218	2.497	0.002	0.049	1.989	19.838
1941-1974	0.011	0.034	0.744	4.312	0.002	0.047	0.973	21.066
1900-1920	0.007	0.031	0.442	7.205	0.002	0.052	1.364	12.484
1921-1940	0.009	0.039	0.065	0.122	0.002	0.044	3.012	33.004
1941-1960	0.009	0.033	0.968	4.761	0.002	0.039	0.877	19.501
1961-1974	0.013	0.035	0.449	4.019	0.003	0.053	-1.429	21.509
1978-2000	0.019	0.090	1.442	11.677	0.004	0.063	-1.779	40.932
2001-2020	0.001	0.046	-1.232	4.008	0.0004	0.035	0.389	19.761
1989-2010	0.005	0.050	-0.099	2.211	0.002	0.054	-5.215	185.55

Notes: Appendix A reports average return, standard deviation, skewness and kurtosis for each calendar month, summer months (May-October), winter months (Nov-April), semesters, quarters, weeks and the entire year.
Source: Own elaboration.

Appendix B – OLS regressions: Risk Premiums

Sample Period	January		February		March		April	
	beta	**t-stat**	**beta**	**t-stat**	**beta**	**t-stat**	**beta**	**t-stat**
1900-2020	0.021	3.280***	0.007	1.500	-0.0003	-0.057	0.008	1.821
1900-1974	0.013	3.506***	0.006	1.469	0.003	0.708	0.006	1.419
1978-2020	0.035	2.115**	0.009	0.831	-0.005	-0.441	0.011	1.171
1900-1940	0.014	2.389**	0.012	2.525**	0.014	2.444**	0.009	1.941*
1941-1974	0.012	2.713***	-0.001	-0.201	-0.011	-3.116***	0.002	0.251
1900-1920	0.012	1.109	0.007	1.531	0.012	2.232**	0.011	2.133**
1921-1940	0.016	3.525***	0.016	2.037**	0.016	1.557	0.007	0.872
1941-1960	0.012	2.059**	-0.008	-1.163	-0.010	-2.255**	0.001	0.199
1961-1974	0.011	1.695*	0.009	0.732	-0.012	-2.077**	0.002	0.151
1978-2000	0.052	1.723*	0.015	0.851	-0.006	-0.333	0.004	0.278
2001-2020	0.017	1.731*	0.002	0.169	-0.004	-0.293	0.018	2.423**
1989-2010	0.017	1.565	0.014	1.176	0.002	0.154	0.009	0.796

Sample Period	May		June		July		August	
	beta	**t-stat**	**beta**	**t-stat**	**beta**	**t-stat**	**beta**	**t-stat**
1900-2020	-0.004	-0.934	-0.012	-3.207***	-0.016	-4.354***	-0.001	-0.375
1900-1974	-0.003	-0.747	-0.010	-2.332**	-0.018	-4.988***	0.002	0.556
1978-2020	-0.004	-0.554	-0.015	-2.092**	-0.012	-1.475	-0.007	-0.856
1900-1940	-0.006	-1.182	-0.007	-1.097	-0.019	-3.537***	-0.001	-0.131
1941-1974	0.001	0.101	-0.013	-2.453**	-0.017	-3.580***	0.005	1.243
1900-1920	-0.0004	-0.049	0.004	0.606	-0.019	-2.714***	-0.008	-1.168
1921-1940	-0.013	-1.915*	-0.017	-1.753*	-0.018	-2.323**	0.007	0.802
1941-1960	-0.005	-0.485	-0.011	-1.788*	-0.025	-3.950***	0.005	0.951
1961-1974	0.010	1.539	-0.016	-1.713*	-0.005	-0.852	0.006	0.789
1978-2000	-0.011	-0.943	-0.016	-1.429	-0.008	-0.660	-0.002	-0.145
2001-2020	0.003	0.280	-0.014	-1.593	-0.015	-1.735*	-0.013	-1.503
1989-2010	-0.005	-0.446	-0.018	-1.816*	-0.002	-0.264	-0.009	-0.903

Sample Period	September		October		November		December	
	beta	**t-stat**	**beta**	**t-stat**	**beta**	**t-stat**	**beta**	**t-stat**
1900-2020	0.011	2.005**	-0.004	-0.685	-0.006	-1.030	-0.005	-0.980
1900-1974	0.011	3.037***	-0.007	-1.500	0.002	0.487	-0.005	-1.221
1978-2020	0.010	0.770	0.001	0.062	-0.019	-1.506	-0.003	-0.295
1900-1940	0.009	1.734*	-0.015	-2.714***	-0.002	-0.390	-0.007	-1.514
1941-1974	0.013	2.747***	0.004	0.659	0.007	1.388	-0.002	-0.295
1900-1920	0.003	0.456	-0.008	-1.089	-0.009	-1.180	-0.004	-1.004
1921-1940	0.016	1.834*	-0.023	-2.805***	0.004	0.420	-0.010	-1.203
1941-1960	0.025	4.329***	0.007	0.797	0.014	2.036**	-0.005	-0.717
1961-1974	-0.005	-0.812	0.001	0.057	-0.003	-0.350	0.002	0.170
1978-2000	0.022	0.998	0.002	0.097	-0.038	-1.774*	-0.013	-0.646
2001-2020	-0.004	-0.445	0.0005	0.034	0.003	0.391	0.008	1.090
1989-2010	-0.005	-0.358	-0.008	-0.584	-0.001	-0.159	0.006	0.900

Sample Period	Halloween effect		1st semester		2nd semester	
	beta	**t-stat**	**beta**	**t-stat**	**beta**	**t-stat**
1900-2020	0.008	2.130**	0.006	2.182**	0.002	1.024
1900-1974	0.007	2.764***	0.004	1.543	0.003	1.515
1978-2020	0.008	0.949	0.009	1.454	0.001	0.203
1900-1940	0.012	3.274***	0.011	2.761***	-0.002	-0.927
1941-1974	0.002	0.525	-0.003	-0.805	0.010	3.589***
1900-1920	0.009	2.097**	0.014	2.766***	-0.004	-1.425
1921-1940	0.015	2.483**	0.008	1.286	-0.0004	-0.087
1941-1960	0.002	0.344	-0.006	-1.225	0.010	2.772***
1961-1974	0.003	0.396	0.001	0.186	0.011	1.130
1978-2000	0.004	0.257	0.010	2.401**	0.004	0.443
2001-2020	0.013	1.972**	0.007	0.953	-0.002	-0.363
1989-2010	0.014	1.690*	0.006	0.816	-0.003	-0.468

Sample Period	1st quarter		2nd quarter		3rd quarter		4th quarter	
	beta	**t-stat**	**beta**	**t-stat**	**beta**	**t-stat**	**beta**	**t-stat**
1900-2020	0.011	3.272***	-0.003	-1.036	-0.003	-0.736	-0.005	-1.535
1900-1974	0.009	2.987***	-0.003	-0.965	-0.002	-0.711	-0.004	-1.396
1978-2020	0.016	1.925*	-0.004	-0.519	-0.004	-0.426	-0.008	-0.991
1900-1940	0.016	3.915***	-0.002	-0.403	-0.004	-0.918	-0.010	-3.018***
1941-1974	0.000	-0.024	-0.004	-0.992	0.0005	0.130	0.004	0.929
1900-1920	0.013	2.475**	0.006	1.134	-0.010	-1.616	-0.008	-2.026**
1921-1940	0.019	3.100***	-0.009	-1.444	0.002	0.242	-0.012	-2.133**
1941-1960	-0.002	-0.553	-0.006	-0.987	0.002	0.414	0.007	1.203
1961-1974	0.003	0.447	-0.002	-0.262	-0.002	-0.298	0.000	0.004
1978-2000	0.024	1.874*	-0.009	-0.834	0.005	0.346	-0.020	-1.414
2001-2020	0.006	0.686	0.003	0.375	-0.013	-1.887*	0.005	0.598
1989-2010	0.013	1.459	-0.006	-0.709	-0.006	-0.751	-0.001	-0.177

Notes: Table presents the coefficients estimates and the t-statistics of the regression in a form of $R_t = \alpha_0 + \beta_i D_{it} + e_t$, where R_t is the continuously compounded monthly risk premium, D_{it} is the dummy variable that that assumes the value 1 when the condition we are analysing is verified and 0 otherwise. Newey-West (1987) heteroskedasticity and autocorrelation adjusted standard errors are used to calculate p-values as reported next to the coefficients. ***: significant at the 1 percent level; **: significant at the 5 percent level; *: significant at the 10 percent level. **Source:** Own elaboration.

Appendix C – GARCH (1,1) regressions and K-W test statistics

Sample Period	January		K-W	February		K-W
	beta	**t-stat**		**beta**	**t-stat**	
1900-1974	0.010	3.530***	13.573***	0.005	1.907*	1.964
1978-2020	0.018	2.696***	5.635**	0.009	1.418	1.235
1900-1940	0.008	2.146**	7.639***	0.008	2.073**	3.811*
1941-1974	0.012	2.530**	5.807**	0.002	0.545	0.002
1900-1920	0.004	1.251	1.136	0.009	2.304**	2.554
1921-1940	0.014	0.907	5.450**	0.009	0.958	2.006
1941-1960	0.010	1.718*	3.155*	-0.003	-0.493	1.210
1961-1974	0.010	1.487	2.920*	0.010	1.565	1.562
1978-2000	0.013	1.384	2.104	0.016	1.583	1.693
2001-2020	0.020	2.020**	4.047**	0.003	0.443	0.026
1989-2010	0.021	2.742***	3.011*	0.014	1.721*	0.730

Sample Period	March		K-W	April		K-W
	beta	**t-stat**		**beta**	**t-stat**	
1900-1974	0.010	3.530***	0.103	0.005	1.637	3.009*
1978-2020	0.001	0.178	0.060	0.008	0.986	1.187
1900-1940	0.004	1.012	3.543*	0.008	1.939*	5.797**
1941-1974	-0.011	-2.384**	6.731***	0.002	0.508	0.001
1900-1920	0.005	1.117	3.328*	0.004	1.246	3.328*
1921-1940	0.008	1.160	1.748	0.007	0.906	1.829
1941-1960	-0.008	-1.470	2.875*	0.002	0.280	0.029
1961-1974	-0.011	-1.956*	4.019**	0.013	3.033***	0.064
1978-2000	0.009	0.726	0.143	0.004	0.378	0.031
2001-2020	-0.002	-0.287	0.000	0.010	0.998	2.343
1989-2010	-0.005	-0.478	0.024	0.005	0.491	0.662

Sample Period	May		K-W	June		K-W
	beta	**t-stat**		**beta**	**t-stat**	
1900-1974	-0.004	-1.356	2.186	-0.006	-2.193**	7.506***
1978-2020	-0.003	-0.510	0.203	-0.018	-2.724***	3.586*
1900-1940	-0.008	-0.008**	3.709*	-0.005	-1.582	3.070*
1941-1974	0.002	0.552	0.001	-0.006	-1.558	4.819**
1900-1920	-0.005	-1.493	1.674	-0.007	-1.762**	0.078
1921-1940	-0.010	-1.285	2.343	-0.003	-0.493	4.959**
1941-1960	0.001	0.326	1.695	-0.001	-0.303	1.721
1961-1974	0.012	1.756*	2.447	-0.008	-1.236	3.882**
1978-2000	0.001	0.109	0.268	-0.018	-1.762*	1.765
2001-2020	-0.007	-0.814	0.009	-0.015	-1.762*	2.211
1989-2010	-0.009	-1.019	0.351	-0.015	-1.834*	2.629

Sample Period	July		K-W	August		K-W
	beta	**t-stat**		**beta**	**t-stat**	
1900-1974	-0.012	-4.364***	24.058***	0.003	0.834	0.909
1978-2020	-0.009	-1.111	1.209	-0.005	-0.693	0.257
1900-1940	-0.014	-3.874***	14.170***	0.001	0.159	0.000
1941-1974	-0.013	-2.888***	10.047***	0.005	1.043	1.758
1900-1920	-0.011	-3.403***	10.257***	-0.002	-0.521	2.192
1921-1940	-0.013	-1.418	5.264**	0.005	0.582	1.039
1941-1960	-0.017	-3.122***	11.751***	0.008	1.070	1.116
1961-1974	-0.005	-0.580	0.685	0.003	0.489	0.685
1978-2000	-0.007	-0.499	0.049	0.002	0.158	0.282
2001-2020	-0.012	-1.167	2.384	-0.012	-1.505	1.940
1989-2010	-0.004	-0.340	0.000	-0.008	-0.976	0.796

Sample Period	September		K-W	October		K-W
	beta	**t-stat**		**beta**	**t-stat**	
1900-1974	0.008	2.839***	9.650***	-0.004	-1.594	0.914
1978-2020	0.003	0.464	0.085	0.002	0.324	0.026
1900-1940	0.004	0.964	3.028*	-0.007	-1.852*	4.189**
1941-1974	0.012	2.652***	7.520***	-0.001	-0.201	0.799
1900-1920	0.005	1.439	1.836	-0.001	-0.370	0.159
1921-1940	0.008	1.161	2.034	-0.016	-2.226**	5.466**
1941-1960	0.016	4.271***	14.450***	-0.002	-0.408	1.278
1961-1974	0.000	-0.059	0.216	-0.006	-0.763	0.000
1978-2000	0.009	0.848	1.049	-0.013	-1.568	0.465
2001-2020	0.000	0.024	0.339	0.010	0.886	1.060
1989-2010	0.001	0.116	0.357	0.003	0.260	0.164

Sample Period	November		K-W	December		K-W
	beta	**t-stat**		**beta**	**t-stat**	
1900-1974	0.001	0.446	1.086	-0.003	-0.991	2.372
1978-2020	-0.007	-1.069	1.907	0.006	0.732	0.007
1900-1940	-0.001	-0.213	0.004	-0.001	-0.251	1.682
1941-1974	0.002	0.487	2.347	-0.005	-1.134	0.690
1900-1920	0.002	0.747	0.312	-0.001	-0.245	0.185
1921-1940	0.002	0.345	0.453	-0.010	-1.080	1.331
1941-1960	0.001	0.141	4.463**	-0.004	-0.839	0.753
1961-1974	-0.004	-0.527	0.049	-0.008	-1.103	0.032
1978-2000	-0.014	-1.359	3.287*	0.004	0.316	0.072
2001-2020	-0.003	-0.281	0.008	0.006	0.614	0.191
1989-2010	-0.005	-0.540	0.153	0.005	0.498	0.197

Sample Period	Halloween effect		K-W
	beta	**t-stat**	
1900-1974	0.002	0.573	11.036***
1978-2020	0.010	2.742***	3.746*
1900-1940	0.007	3.650***	18.335***
1941-1974	0.000	0.118	0.058
1900-1920	0.005	2.924***	8.615***
1921-1940	0.009	2.121**	10.796***
1941-1960	-0.003	-0.932	0.001
1961-1974	0.002	0.573	0.216
1978-2000	0.011	1.789*	0.437
2001-2020	0.011	2.347**	5.063**
1989-2010	0.011	2.169**	3.330*

Sample Period	1st semester		2nd semester		K-W
	beta	**t-stat**	**beta**	**t-stat**	
1900-1974	0.002	1.490	0.005	4.265***	1.610
1978-2020	0.004	1.033	0.005	1.582	1.838
1900-1940	0.005	2.213**	0.003	2.085**	8.589***
1941-1974	0.000	-0.009	0.008	4.273***	1.882
1900-1920	0.002	1.116	0.004	2.965***	6.821***
1921-1940	0.008	1.737*	0.004	1.277	2.174
1941-1960	-0.001	-0.441	0.004	1.953*	4.423**
1961-1974	0.008	2.126**	0.009	3.448***	0.212
1978-2000	0.006	1.005	-0.002	-0.537	0.627
2001-2020	0.004	0.768	0.006	1.552	1.403
1989-2010	0.003	0.591	0.007	1.681*	0.328

Sample Period	1st quarter		K-W	2nd quarter		K-W
	beta	**t-stat**		**beta**	**t-stat**	
1900-1974	0.005	2.803	9.214	-0.002	-1.048	2.482
1978-2020	0.012	2.812	5.624	-0.006	-1.345	0.642
1900-1940	0.008	3.292	17.677	-0.001	-0.574	0.658
1941-1974	0.001	0.361	0.021	-0.001	-0.381	2.071
1900-1920	0.005	2.453	8.217	-0.003	-1.402	0.026
1921-1940	0.012	2.306	10.484	-0.003	-0.578	2.357
1941-1960	-0.002	-0.683	0.423	0.001	0.239	3.161
1961-1974	0.004	1.018	0.375	0.007	1.899	0.008
1978-2000	0.019	2.810	1.138	-0.006	-0.876	1.138
2001-2020	0.010	1.886	1.960	-0.005	-0.934	0.001
1989-2010	0.013	2.412	2.416	-0.009	-1.454	0.798

Sample Period	3rd quarter		K-W	4th quarter		K-W
	beta	**t-stat**		**beta**	**t-stat**	
1900-1974	0.000	-0.176	0.291	-0.003	-1.504	0.861
1978-2020	-0.005	-1.095	0.704	0.000	0.104	0.526
1900-1940	-0.003	-1.107	1.654	-0.003	-1.355	4.392
1941-1974	0.002	0.587	0.328	-0.002	-0.655	1.034
1900-1920	-0.002	-1.063	4.517	0.000	0.047	0.785
1921-1940	0.000	0.085	0.009	-0.009	-2.018	3.238
1941-1960	0.004	1.175	0.833	-0.003	-0.864	2.298
1961-1974	-0.001	-0.216	0.088	-0.009	-2.048	0.058
1978-2000	0.001	0.196	0.725	-0.011	-1.664	3.114
2001-2020	-0.934	-1.952	5.044	0.005	0.238	0.771
1989-2010	-0.005	-0.815	0.908	0.001	0.190	0.085

Notes: Table presents the coefficients estimates, the t-statistics of the calendar months, the Halloween effect, quarters and semester. Estimations were computed with the GARCH (1,1) model. Seasonality is also tested using a Kruskal-Wallis (K-W) rank-based non-parametric equality test. ***: significant at the 1 percent level; **: significant at the 5 percent level; *: significant at the 10 percent level. **Source:** Own elaboration.

Appendix D – OLS Robust estimations

Sample Period	January		February		March		April	
	beta	**t-stat**	**beta**	**t-stat**	**beta**	**t-stat**	**beta**	**t-stat**
1900-2020	0.012	3.662***	0.006	1.902*	0.001	0.291	0.006	1.759*
1900-1974	0.012	3.459***	0.005	1.337	-0.003	-0.744	0.006	1.735*
1978-2020	0.017	2.229**	0.011	1.427	0.007	0.925	0.007	0.956
1900-1940	0.012	2.637***	0.007	1.499	0.007	1.564	0.011	2.403**
1941-1974	0.011	2.320**	0.001	0.169	-0.011	-2.358**	-0.001	-0.174
1900-1920	0.006	1.499	0.006	1.632	0.005	1.337	0.005	1.283
1921-1940	0.017	1.906*	0.014	1.468	0.014	1.521	0.011	1.248
1941-1960	0.011	1.694*	-0.007	-1.047	-0.009	-1.341	-0.003	-0.422
1961-1974	0.012	1.604	0.013	1.753*	-0.016	-2.236**	0.004	0.530
1978-2000	0.019	1.519	0.028	2.234**	0.009	0.710	-0.002	-0.124
2001-2020	0.019	2.025**	-0.001	-0.108	0.004	0.379	0.014	1.441
1989-2010	0.020	1.965**	0.011	1.076	-0.002	-0.237	0.008	0.790

Sample Period	May		June		July		August	
	beta	**t-stat**	**beta**	**t-stat**	**beta**	**t-stat**	**beta**	**t-stat**
1900-2020	-0.006	-1.717*	-0.012	-3.474***	-0.012	-3.613***	0.003	0.768
1900-1974	-0.006	-1.772*	-0.010	-2.923***	-0.015	-4.500***	0.004	1.220
1978-2020	-0.004	-0.522	-0.014	-1.824*	-0.008	-1.096	-0.005	-0.695
1900-1940	-0.010	-2.171**	-0.010	-2.213**	-0.017	-3.630***	0.002	0.482
1941-1974	-0.001	-0.164	-0.010	-2.052**	-0.013	-2.736***	0.006	1.217
1900-1920	-0.008	-2.114**	-0.005	-1.170	-0.011	-2.926***	-0.005	-1.224
1921-1940	-0.012	-1.348	-0.024	-2.636***	-0.020	-2.143**	0.010	1.088
1941-1960	-0.011	-1.647*	-0.008	-1.225	-0.019	-3.000***	0.006	0.923
1961-1974	0.012	1.537	-0.013	-1.694*	-0.006	-0.793	0.007	0.859
1978-2000	-0.007	-0.552	-0.011	-0.909	-0.004	-0.332	0.003	0.210
2001-2020	-0.003	-0.263	-0.016	-1.658*	-0.013	-1.303	-0.016	-1.647*
1989-2010	-0.007	-0.649	-0.018	-1.734*	0.001	0.072	-0.009	-0.867

Sample Period	September		October		November		December	
	beta	**t-stat**	**Beta**	**t-stat**	**beta**	**t-stat**	**beta**	**t-stat**
1900-2020	0.007	2.195**	-0.002	-0.620	0.001	0.185	-0.004	-1.039
1900-1974	0.009	2.778***	-0.003	-0.807	0.005	1.543	-0.005	-1.445
1978-2020	0.000	-0.008	-0.003	-0.373	-0.007	-0.889	0.002	0.285
1900-1940	0.007	1.404	-0.008	-1.676*	0.003	0.584	-0.005	-1.116
1941-1974	0.012	2.516**	0.005	1.023	0.008	1.650*	-0.006	-1.120
1900-1920	0.005	1.157	0.001	0.296	0.000	0.059	-0.001	-0.292
1921-1940	0.013	1.368	-0.022	-2.359**	0.008	0.845	-0.010	-1.078
1941-1960	0.024	3.902***	0.009	1.409	0.014	2.239**	-0.005	-0.849
1961-1974	-0.004	-0.464	-0.001	-0.130	-0.001	-0.088	-0.004	-0.522
1978-2000	0.008	0.645	-0.020	-1.620	-0.013	-1.078	-0.001	-0.078
2001-2020	-0.008	-0.809	0.014	1.494	-0.002	-0.157	0.004	0.397
1989-2010	-0.010	-0.945	0.007	0.713	-0.004	-0.346	0.004	0.383

Sample Period	Halloween effect		1st semester		2nd semester	
	beta	**t-stat**	**beta**	**t-stat**	**beta**	**t-stat**
1900-2020	0.007	3.676***	0.003	1.346	0.006	4.575***
1900-1974	0.006	3.211***	0.001	0.778	0.007	5.435***
1978-2020	0.011	2.557**	0.007	1.603	0.003	1.063
1900-1940	0.011	4.233***	0.006	2.176**	0.004	2.410**
1941-1974	0.000	0.179	-0.004	-1.350	0.011	5.553***
1900-1920	0.006	2.840***	0.003	1.563	0.004	2.857***
1921-1940	0.017	3.474***	0.007	1.421	0.005	1.315
1941-1960	0.000	0.024	-0.008	-2.150**	0.011	4.361***
1961-1974	0.002	0.425	0.003	0.720	0.010	3.332***
1978-2000	0.010	1.377	0.008	1.211	0.006	1.187
2001-2020	0.012	2.337**	0.006	1.109	0.002	0.641
1989-2010	0.011	1.867*	0.003	0.509	0.004	0.963

Sample Period	1st quarter		2nd quarter		3rd quarter		4th quarter	
	beta	**t-stat**	**beta**	**t-stat**	**beta**	**t-stat**	**beta**	**t-stat**
1900-2020	0.008	3.737***	-0.005	-2.092**	-0.001	-0.599	-0.002	-0.959
1900-1974	0.006	2.647***	-0.004	-1.753*	-0.001	-0.335	-0.001	-0.572
1978-2020	0.014	2.848***	-0.004	-0.846	-0.006	-1.197	-0.003	-0.596
1900-1940	0.011	3.612***	-0.003	-1.028	-0.003	-1.112	-0.004	-1.359
1941-1974	0.000	-0.039	-0.005	-1.554	0.002	0.662	0.003	0.924
1900-1920	0.007	2.765***	-0.002	-0.922	-0.004	-1.640	0.000	0.021
1921-1940	0.019	3.238***	-0.009	-1.589	0.000	0.066	-0.010	-1.726*
1941-1960	-0.002	-0.491	-0.009	-2.070**	0.004	1.091	0.006	1.573
1961-1974	0.003	0.548	0.002	0.346	-0.002	-0.379	-0.002	-0.448
1978-2000	0.022	2.723***	-0.008	-1.037	0.002	0.285	-0.013	-1.684*
2001-2020	0.009	1.525	-0.001	-0.212	-0.015	-2.407**	0.006	1.017
1989-2010	0.011	1.661*	-0.007	-0.987	-0.007	-1.067	0.003	0.450

Notes: Table presents the coefficients estimates, the t-statistics of the robust regression in a form of $R_t = \alpha_0 + \beta_i D_{it} + e_t$, where R_t is the continuously compounded monthly return, D_{it} is the dummy variable that that assumes the value 1 when the condition we are analysing is verified and 0 otherwise. The robust regressions are based on M-estimation introduced by Huber (19873). ***: significant at the 1 percent level; **: significant at the 5 percent level; *: significant at the 10 percent level. **Source:** Own elaboration.

Appendix E - Description of documented models

Model	Jan	Feb	March	Apr	May	June	July	Aug	Sep	Oct	Nov	Dec
0000	0	0	0	0	0	0	0	0	0	0	0	0
0037	0	0	1	0	0	1	0	0	0	0	0	0
0101	0	0	1	0	0	1	1	0	0	0	0	0
0119	0	1	1	0	1	1	1	0	0	0	0	0
0485	0	0	1	0	0	1	1	1	1	0	0	0
0503	0	1	1	0	1	1	1	1	1	0	0	0
0609	0	0	0	0	0	1	1	0	0	1	0	0
1009	0	0	0	0	1	1	1	1	1	1	0	0
1249	0	0	0	0	0	1	1	1	0	0	1	0
1253	0	0	1	0	0	1	1	1	0	0	1	0
2673	0	0	0	0	1	1	1	0	0	1	0	1
2753	0	0	0	0	0	0	1	1	0	1	0	1
3121	0	0	0	0	1	1	0	0	0	0	1	1
3777	0	0	0	0	0	0	1	1	0	1	1	1
4094	0	1	1	1	1	1	1	1	1	1	1	1
4095	1	1	1	1	1	1	1	1	1	1	1	1

Notes: The table shows a description of the monthly stock-cash allocation strategies reported as "best" or "most significant" models in Table 14. The values *"1"*and '*0"* indicate a cash and stock allocation in a given month, respectively. **Source:** Own elaboration.