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Seasonal Equity Carry Trades Between the US and the UK

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1. INTRODUCTION

Burnside *et al.* in 2006 and then in 2007 defined the hypothesis of Uncovered Interest Parity, which implies that the difference in interest rates between two countries will equal the expected change in the foreign exchange rate between the two currencies, over the same period. Nonetheless this hypothesis has been proven wrong by many scholars: Meese and Rogoff (1983), Hansen and Hodrick (1980), Cumby and Obstfeld (1981), and most famously Fama (1984). The latter indeed, by testing a model for the joint measurement of variation in the premium and the expected spot rate components of forward rates, found that, as both components vary through time, premia and expected future spot rate components are negatively correlated, rather than positively. Following literature continues also to find that currencies in countries with high interest rates tend to appreciate with respect to currencies in countries with low interest rates (Clarida *et al.*, 2009). These findings demonstrate that investors can make systematic profits by selling the low-return currency and buying the high-return one. This type of arbitrage opportunity is referred to as Interest Carry Trades.

These hypotheses can similarly be applied to the stock market. In this case the theories may be named Uncovered Equity Parity and Equity Carry Trades. When two markets with different currencies display divergence in stock returns, UEP-supporting scholars would expect the average investor to disinvest from the well performing market (defined as the foreign market), in order to protect themselves from risk, and move to the worse performing one (the domestic market). The sale of the foreign holdings leads to a depreciation of the foreign currency, bringing the market back to equilibrium.

This paper aims at testing the Equity Carry Trades hypothesis which contrasts with UEP by stating that when facing an outstandingly well-performing market, and a badly-performing one, investors may seize the profit opportunities that arise from selling the low-return equities and from buying the high-return ones, generating an appreciation of the currency in the high stock return country. While interest carry trades tackle interest rate discrepancies in different countries, equity carry trades address different countries' equity return differentials. The markets that will be analyzed in this paper are the American and British ones. This research thus serves two purposes. The first is that of providing an efficient method to address the still lightly explored topic of Equity Carry Trades. The second objective is that of offering an empirical analysis on the seasonality of the American and British stock and forex markets, and on the opportunity to actually engage in Equity Carry Trades by exploiting one of the most important and most exploited currency pair on the market. These objectives aim at contributing to the research on the subject of Equity Carry Trades, since literature in this field is still little, by increasing the possibilities to address the matter and the amount of research on different currency pairs. Many research papers that address the topic of seasonality deal with numerous currency pairs all at once, or with the behavior of a single country. This paper offers an insight, both methodological and empirical on the GBP/USD exchange market.

In order to investigate the presence of Equity Carry Trades, this research will analyze seasonal effects in the considered markets: in particular, a January effect in the stock markets, and a January and a December effect in the foreign exchange market, according to previous literature, but also any apparent effects in other months of the year. Furthermore, the correlation between seasonal behaviors of the considered stock markets and the corresponding exchange rate will be addressed. Given the existence of seasonality in both areas proven by previous research, this paper aims at concluding that such correlation exists, and that Equity Carry Trades are and can be performed in this kind of dynamic.

The research will be carried out by considering an index for each market, the S&P 500 and the FTSE 100, more specifically, plus the behavior of the GBP/USD exchange rate. Data will be monthly, starting from 1986 until the pre-pandemic years, and the analysis will rely on an investigation of equity capital flows between the two countries, which function as a transmission channel between the currency exchange and the stock markets. The considered data begins in January 1986, since the FTSE 100 index was launched on January 3rd, 1984 (it was built to replace the price-weighted FT30 Index in the London Stock Exchange), and carries on until the end of 2019. The closing date has been selected because, at the time this research is being carried out, the effects of the Covid-19 crisis still have to settle and are too fresh for a sound judgement of the economic situation.

This work will be carried out on four time series, then reduced to three: the two stock market indices (which will be studied as the stock return differential of the two), the GBP/USD exchange rate, and the net equity capital flows from the USA to the United Kingdom. The analysis will begin with some descriptive statistics of the time series, followed by a linear analysis of seasonal behavior in the foreign exchange market, and in stock return differentials. Finally, the Census X-11 algorithm will be used as a non-linear approach to the study of seasonality. In order to understand the behavior of Equity Carry Trades, net equity flows will be accounted for: they will be studied similarly to stock return differentials and exchange rate returns, through some descriptive statistics, and a linear and a non-linear seasonal analysis. Equity flows will be studied in terms of gross and net amounts, and according to the results of break tests. The behavior of the exchange rate is of interest, as the involved currencies represent two of the most important media of exchange in the market. A similar study on euros and dollars has been indeed already carried out by Girardin and Salimi (2019). The scholars have studied the possibility for Equity Carry Trades at the turn of the year between the United States and Germany. The used datasets went from 1971 to 2017, thus they compared the Deutsche mark to the US dollar for the first part of their time series, and the euro to the dollar for the second part. The study employs a Markov-switching model, and it concludes that January and December display respectively higher and lower returns in the US with respect to Germany, and that they are associated with a dollar appreciation in January and depreciation in December, and with matching capital flows between the two countries.

What will be found will be that, despite the existence of January and December effects in the stock and forex markets, the most interesting month will be that of March, in the specific case of this currency pair. The paper will address the seasonal components in the month of March, to demonstrate how they are analogous between the stock return differentials time series and that of exchange rate returns. Net equity flows will hardly support the hypothesis of Equity Carry

Trades; nonetheless, it will be found that this dataset is highly influenced by a number of factors that do not allow it to be purely accountable in this research.

The paper will first provide a brief review of Previous Literature on the subject of seasonality in Section 2; then it will carry out a through explanation of the used Data and Methodology (Section 3), followed by the Empirical Results of the linear, non-linear, parametric and non-parametric tests of seasonality for all time series (Section 4). Finally, Conclusions will be drawn in Section 5.

2. REVIEW OF LITERATURE

But what is seasonality? It is a characteristic of time series, by which data displays some regular changes, that recur every calendar year. Any fluctuation or pattern that is predictable and recurs over a one-year period is said to be seasonal (Investopedia). The phenomenon of seasonality in economics was derived from meteorology, mainly thanks to Buys-Ballot who studied periodic temperature variations in 1847 (Buys-Ballot, 1847). Subsequently, around the end of the nineteenth century, economists started studying unobserved components in time series with the idea of revealing cycles, which would allow them to predict economic crises. The main names in the literature of economic seasonality are Persons (1919), King (1924), and Macaulay (1931), who were among the first to address time series decomposition. By the 1950s, seasonal adjustment started to be applied at the industrial level, thanks to the revolution of computers (Eurostat, 2018).

More specifically, on the US and UK stock markets, Floros and Salvador (2014) conducted an examination of spot and futures returns before and after the 2008 Global Financial Crisis, by considering the FTSE 100 index for the UK, and the S&P 500 and the NASDAQ 100 indices for the US. What they found was that the British market displays some April, November and December seasonal effect, while the American one presents some January, March, July, November and December effects. These findings were partially confirmed by Chen (2013) who investigated the causes that generate the presence of the January effect in the mean returns of common stocks in the US and the UK. What the scholar found was indeed a January effect in both countries, plus an April one in the British market, and a confirmation that her hypothesis, which states that higher returns in January may be explained by greater market volatility, is partially true. The relationship between market return and volatility is explained by the Sharpe Ratio, which represents the average return earned in excess of the risk-free rate, per unit of volatility.

With respect to the currency market, on the other hand, Li *et al.* (2011) researched the monthly seasonality of a number of currencies against the US dollar, UK pound included, from 1972 to 2010. They found that, in general, December (January) is shown to have the highest (lowest) average and median returns, with all currencies reporting positive (negative) returns in December (January). The GBP/USD presents statistically significant negative returns in January and a significant positive December effect. Other months may display unusual return patterns, but no other seasonality is as significant as in December and January.

What can be stated, then, is that previous literature shows that seasonality has been observed in the US stock market with a January effect, in the UK stock market with a January and an April effect, and in the GBP/USD exchange rate in January and December. Past research can be deemed useful in analyzing the phenomenon of Equity Carry Trades.

3. DATA AND METHODOLOGY

3.1. DATA

The datasets that are used in this research, are all constituted by monthly data, that ranges from January 1986 to December 2019. Quotes are end of month for all datasets.

To analyze the stock markets of the United States and of the United Kingdom, the stock indices S&P 500 and FTSE 100 are considered. The S&P 500 quotes have been downloaded from Investing.com, whereas those of the FTSE 100 are taken from the Fred website, of the St. Louis Fed. After computing the returns of the two indices, based on their end of the month closing prices, the differentials of returns are defined, by subtracting the returns on the S&P 500 from those on the FTSE 100. This direction is chosen because this work will address inflows into the UK, and outflows from the US. Figure 1 displays the stock markets return differentials.

Following, returns on the GBP/USD exchange rate are computed, to remain consistent with the direction of the net equity flows and stock market return differentials. Again, the exchange rates were downloaded from Investing.com prior to being transformed to returns. Returns are displayed in Figure 2, while Figure 3 shows the movements of the quotes in the considered period, according to historical events too.

Finally, after downloading the data on gross equity flows between the United States and the United Kingdom, their net was computed by summing all flows from the US into the UK (both US Corporate stock and British stock purchases from British investors) and by subtracting to those all flows from the UK into the US (both US Corporate and British stock purchases from American investors).

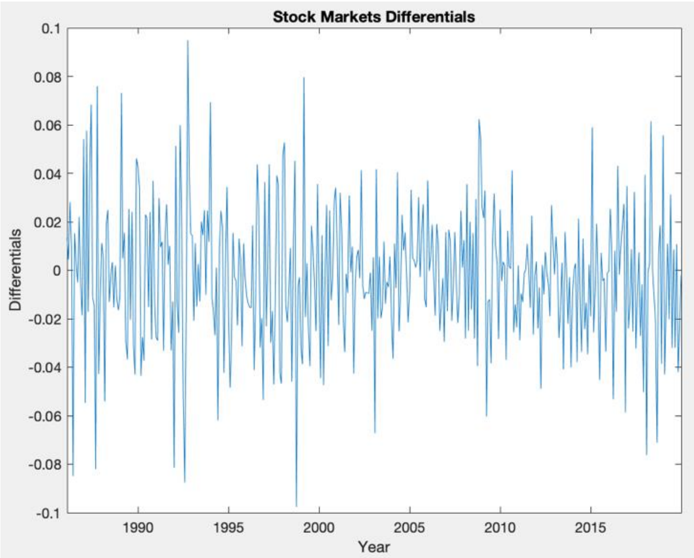


Figure 1 - Stock Markets Return Differentials (1986-2019)

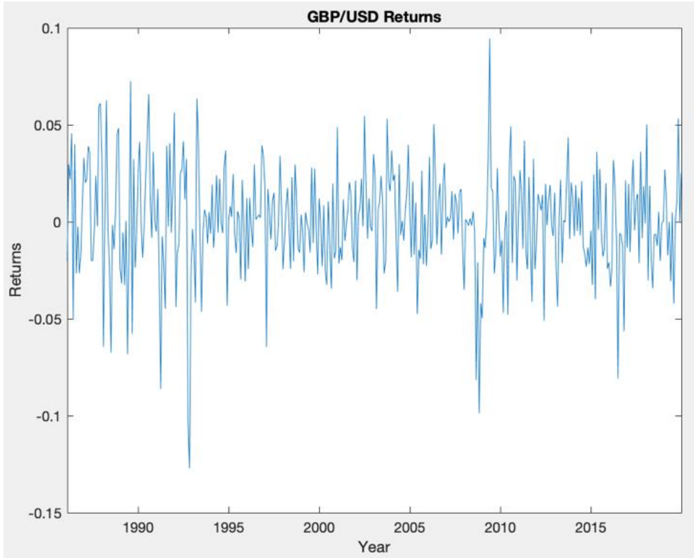


Figure 2 - GBP/USD Exchange Rate Returns (1986-2019)

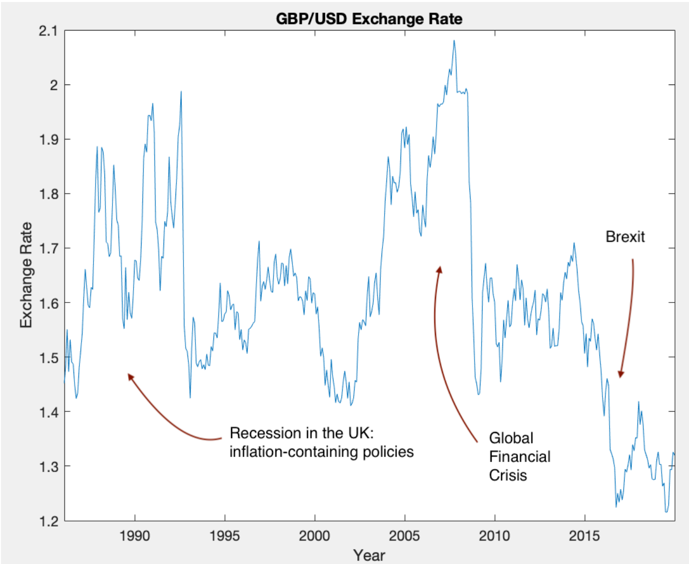


Figure 3 - GBP/USD Exchange Rates (1986-2019)

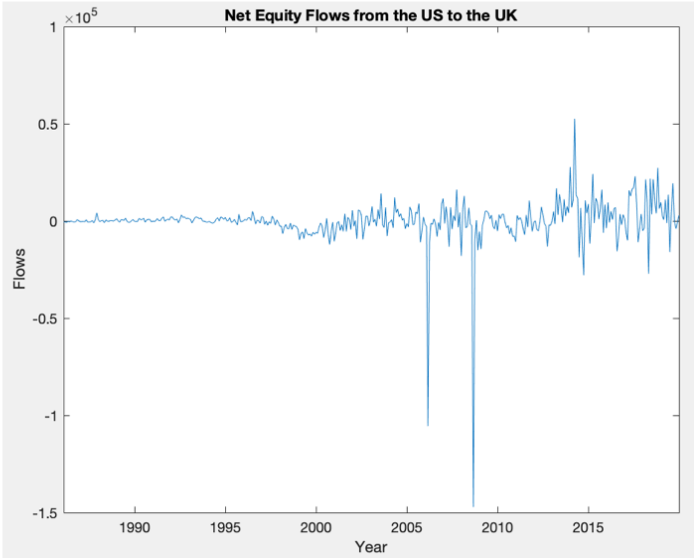


Figure 4 - Net Equity Flows from the US to the UK (1986-2019)

Equity capital flows, in terms of gross purchases and sales by both American Residents and "Foreigners", were provided by the Treasury International Capital (TIC) System of the US Government Treasury. The direction of flows remains consistent with the forex rate and the direction of stock market return differentials. Net equity flows, from the US to the UK are displayed in Figure 4.

3.2. METHODOLOGY

3.2.1. DESCRIPTIVE STATISTICS

In order to prepare the data for the research, some descriptive statistics are performed. The analysis is started by plotting all the available data (including both indices and forex prices, they can be found in Appendix 1, Figures A 1 and A 2), and by performing some first hypotheses testing:

- Jarque-Bera Test for normality (Jarque and Bera, 1987);
- Unit root tests: Augmented Dickey-Fuller Test (Dickey and Fuller, 1979), Phillips and Perron Test (1988), KPSS Test (Kwiatkowski *et al.*, 2002), Ng and Perron Test (2001);
- Test for Structural Breaks.

In the Jarque-Bera Test, the null hypothesis is that the analyzed vector follows a normal distribution, in this case the hypothesis is that the three time series (stock return differentials, exchange rate returns and net equity flows) are normally distributed. The tests for all time series reject the hypothesis of normality, meaning that no considered data sample displays a normal distribution.

The Augmented Dickey-Fuller Test tests the hypothesis that a unit root exists in the sample, meaning that the time series cannot be stationary. This test results in the hypothesis being rejected for all three datasets, meaning that they are all stationary according to this first approach.

Phillips-Perron Test similarly addresses the issue of stationarity. The difference between this test and the Augmented Dickey-Fuller one lies in how they each address serial correlation. While ADF uses a parametric autoregression to approximate the structure of errors, the Phillips-Perron test is non-parametric, and thus ignores the issue of serial correlation. The null hypothesis is again that a unit root exists in the sample. The outcome of this test, as much as the Augmented Dickey-Fuller one, confirms that all three time series are stationary.

Finally, the KPSS Test approaches the topic in the opposite way: the null hypothesis is stationarity, while the alternative implies the presence of a unit root. In this case, nonetheless, the test reveals that only stock return differentials and exchange rate returns seem to be stationary, while, in the case of net equity flows, the null hypothesis cannot be rejected.

The Ng and Perron Test is another test that investigates the presence of unit roots, but, differently from the previous three, it takes into account the existence of structural breaks. This peculiarity makes this test more appropriate for this research, as time series as the ones described are likely to present structural breaks. The test is performed on: FTSE 100 returns, S&P 500 returns, stock market return differentials, GBP/USD exchange rate returns, and net equity flows. The null hypothesis in this test is that the time series has a unit root, and it can be rejected if each test statistic of the resulting four is smaller than the corresponding critical values (the four test statistics are MZ_α, MZ_t, MSB, MP_T, the so-called M tests. Where MZ_α and MZ_t can be viewed as modified versions of the Phillips and Phillips-Perron Z_α and Z_t tests, respectively, and where $MZ_t = MZ_\alpha \, x \, MSB$. These tests provide functionals of sample moments that have the same asymptotic distribution as better-known unit root tests, while the MP_T is important because its limiting distribution coincides with that of the feasible point optimal test considered by Elliot, Rothenberg, and Stock (Ng and Perron, 2001)). In all these tests the t-statistics are always smaller than the critical values, thus the null can be rejected: all time series are stationary. All the descriptive statistics are collected in Table 1.

	Min	Mean	Max	Standard Deviation	Skewness	Kurtosis	Jarque-Bera (1987)
ΔLFTSE100 - ΔLS&P500	-0.098	-0.003	0.095	0.029	0.021	0.675	**7.26
ΔL(GBP-USD)	-0.127	0.000	0.094	0.028	-0.469	1.909	***74.37
NEF	-147.110	-0.060	52.576	11.436	-6.818	85.080	***123,170.00

	ADF (1979)	Phillips and Perron (1988)	KPSS (1992)	Ng and Perron (2001) MZa	Ng and Perron (2001) MZt
ΔLFTSE100 - ΔLS&P500	***-23.840	***-23.840	0.041	***-202.515	***-10.0624
ΔL(GBP-USD)	***-18.879	***-18.879	0.029	***-196.684	***-9.91399
NEF	***-17.640	***-17.640	***0.444	***-200.195	***-10.0047

Table 1 - Descriptive statistics.

*** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level*

ΔLFTSE100 - ΔLS&P500 represents stock return differentials between the British FTSE 100 and the American S&P 500 indices. ΔL(GBP-USD) is the GBP/USD exchange rate return, and NEF stands for Net Equity Flows from the US to the UK.

Sample: January 1986 to December 2019 for all time series.

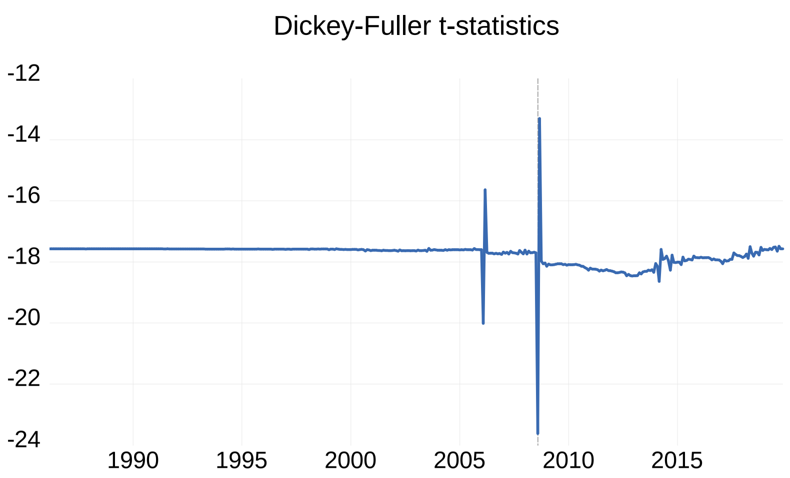


Figure 5 - Dickey-Fuller break test t-statistics on Net Equity Flows.

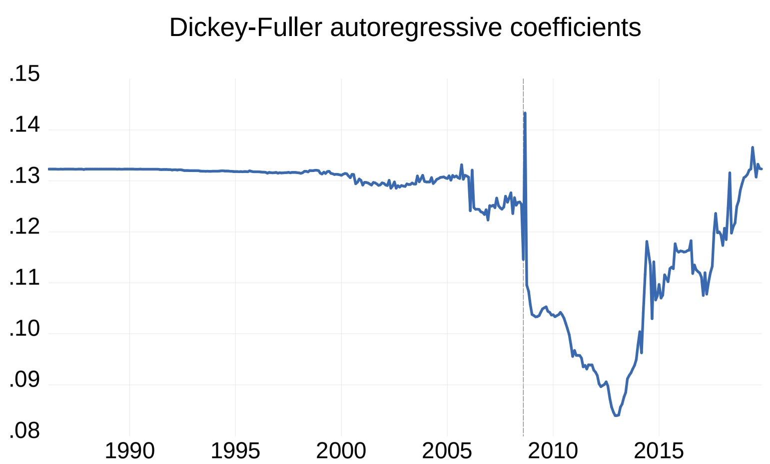


Figure 6 - Dickey-Fuller break test autoregressive coefficients on Net Equity Flows.

Finally, a test for structural breaks is ran. It is called a structural break when a time series abruptly changes at a point in time. This change could involve a change in mean or a change in the other parameters of the process that produce the series (Stata). In this case the analysis involves not only the three datasets that play as main characters in this paper, but also on S&P 500 returns, on FTSE 100 returns, on S&P 500 prices, FTSE 100 prices, and exchange rate quotes. Break tests confirm the stationarity for all variables, exception made for FTSE 100 and S&P 500 prices. In these cases structural breaks are present with a unit root in April 2001 and September 2011, respectively. In the case of Net Equity Flows, there is a break point in August 2008, although with stationarity, that will be taken into consideration later in this research (displayed in Figures 5 and 6).

3.2.2. TESTS OF EQUALITY

After considering the descriptive statistics, parametric and non-parametric tests of equality are performed. In particular:

- ANOVA Test (Fisher, 1920) and Kruskal-Wallis Test (Kruskal and Wallis, 1952);
- Levene's Test (1960) and its non-parametric version (Nordstokke and Zumbo, 2010).

It is important to distinguish between parametric and non-parametric versions of these tests, since, while the former version accounts for normal distributions only, the latter does not assume any distribution in particular, and thus allows for a more open approach. Following, an OLS Regression will be performed.

ANOVA and Kruskal-Wallis tests focus on the equality of the means of independent groups. ANOVA Test is the parametric version of such analysis, while Kruskal-Wallis is the non-parametric one. These tests are here performed by comparing each time series by month, to understand whether the mean of each month is similar to that of the others, or if there is a recurring behavior that differs across times of the year. In Tables 2 to 4 the results of the ANOVA analysis are displayed.

Each of these tests yields a p-Value greater than 0.05, meaning that the null hypothesis of equality of means cannot be rejected. According to the ANOVA Test all months in each time series present similar means.

As previously seen with the Jarque-Bera test, no time series in the sample has a normal distribution, thus it cannot be assumed that all the time series display such equality among months. It is best to run the non-parametric version of the test. The results obtained from the Kruskal Wallis Test are displayed in Table 5. The null of equality of means for stock return differentials and for exchange rate returns can be rejected, but it cannot for net equity flows. In Appendix 1 the graphical representations of this test can be found (Figures A 3, A 4 and A 5), and from these results a first glance at seasonal behavior can be given. Stock return differentials seem to have a low mean for January, and a high one for December. The same is observed in exchange rate returns, where also April shows a mean higher than the other months. In the case of net equity flows, the

ANOVA - ΔLFTSE-ΔS&P

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.014	11	0.001	1.629	0.088	1.813
Within Groups	0.320	396	0.001			
Total	0.334	407				

Table 2 - Stock return differentials ANOVA Test for equality of means.

The null hypothesis of the ANOVA Test states that the means of all months, in this case, are all equal to each other. The null is rejected when the p-Value is lower than the significance level, 0.05 in this case. Another way to reject the null in ANOVA Testing is when the F value is greater than the F crit one.

ANOVA - Δ(GBP-USD)

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.012	11	0.001	1.476	0.138	1.813
Within Groups	0.298	396	0.001			
Total	0.310	407				

Table 3 - Exchange rate returns ANOVA Test for equality of means.

ANOVA - NEF

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	1694907050	11	154082459	1.184	0.296	1.813
Within Groups	5.1537E+10	396	130143748			
Total	5.3232E+10	407				

Table 4 - Net Equity Flows ANOVA Test for equality of means.

hypothesis of equality of means cannot be rejected meaning that signs of seasonality cannot be found, for now.

ANOVA tests generally require a homogeneity assumption: thus, that the population variances of a dependent variable must be equal within all groups. Levene's test serves this purpose of testing the equality of variances. Actually, when dealing with groups that have equal sample sizes, it is not necessary to test for homogeneity, nonetheless, in this paper, this analysis is carried out for completeness.

Levene's test, just like the ANOVA, has both a parametric and a non-parametric version. When performing the parametric test, it is found that the null hypothesis that all variances are equal cannot be rejected in the sets of exchange rates returns, net equity flows and stock return differentials (both according to p-Values and F-Fcrit comparison). To perform Levene's test, residuals of all returns are computed (each return minus the average, in absolute values) and an ANOVA test on residuals is performed.

Again, when performing the non-parametric version of the test, the null cannot be rejected for any of the considered sets (both according to F-Fcrit and p-Values). In this case non normal distributions of data are considered. In order to compute the non-parametric test, each group of data is ranked (stock market differentials, net equity flows and exchange rates) and an ANOVA test on the residuals of the ranks is performed. Results can be found in Table 5.

	Kruskal Wallis	Parametric Levene			Non-parametric Levene		
	Prob > Chi-sq	F	F crit	p-Value	F	F crit	p-Value
ΔLFTSE100 - ΔLS&P500	**0.0323	1.210	1.813	0.278	1.394	1.813	0.173
ΔL(GBP-USD)	**0.0266	0.944	1.813	0.498	1.075	1.813	0.380
NEF	0.391	1.203	1.813	0.282	0.587	1.813	0.840

Table 5 - Kruskal Wallis and Levene's Tests

**** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level*
ΔLFTSE100 - ΔLS&P500 represents stock return differentials between the British FTSE 100 and the American S&P 500 indices. ΔL(GBP-USD) is the GBP/USD exchange rate return, and NEF stands for Net Equity Flows from the US to the UK.
Sample: January 1986 to December 2019 for all time series.

3.2.3. OLS REGRESSION

Ordinary Least Squares regression is one of the most popular statistical techniques used in economics. The first description of the method of least squares was published by Adrien-Marie Legendre in 1805, and it was subsequently justified on statistical grounds by Gauss (1809) and Laplace (1812) (Heyde *et al.*, 2001).

In this paper, the regression is used to linearly analyze the considered time series. The regression is performed by considering 11 monthly dummy variables, and one intercept. Table 6 displays the results of the analysis. Net equity flows will be further analyzed in the following chapter, as break test results will be taken into account.

This linear model estimates seasonality in the months of February and December for stock return differentials, in January for the exchange rate returns, and none for net equity flows. Nonetheless, when estimating linear models for long samples, stability of parameters may be a concern, since the seasonal patterns may mutate over time (Girardin and Salimi, 2019). Thus, it is best to exploit a non-linear model in the analysis of the seasonal patterns concerning these time series. The non-linear model used in this paper to address seasonal behavior is the Census X-11 method.

3.2.4. CENSUS X-11

In order to understand the behavior of the time series, and thus to check whether it is possible to observe a behavior in the seasonality of the two stock markets and in the exchange rate, such that Equity Carry Trades can be exploited, the seasonal component of each time series is extracted. In order to do so, the X-11 method of 1965 (Shiskin *et al.*, 1967) by the US Bureau of the Census is used. Seasonal adjustment methods are generally used to eliminate periodic fluctuations from time series, that hinder the understanding of a basic trend. On the other hand, seasonal adjustment allows the extraction of signals, and this is the purpose it will be used for in this paper. According to the Handbook on

Seasonal Adjustment of 2018, seasonal adjustment shall indeed be considered as an estimation of unobserved components. Thus, four typically unobserved components have been identified:

- T_t: a long term or secular trend;

It is a level estimate for each month that is derived from the surrounding year of observations. This component shows the long-term movement of the time series.

- C_t: a cyclical movement superposed to the trend;
- S_t: a seasonal movement;

Refers to effects that are stable in terms of annual timing, direction and magnitude. These effects are generally caused by natural elements, administrative measures, social, cultural or religious traditions, but also by trading day or moving holiday effects.

- I_t: a residual variation, which represents the unexplained part;

This represents anything that is not included in the other three components, and it can arise from errors, unseasonable weather, natural disasters, strikes, *et cetera* (US Census Bureau).

Decomposition schemes can take different shapes, but nowadays it is important to notice that they also take into account some deterministic components such as the number of working days in the analyzed period (WD_t) or moving holidays effects (HE_t). One example is the additive scheme:

$$X_t = T_t + C_t + S_t + WD_t + HE_t + I_t$$

By studying the seasonal movement of the time series, it will be possible to understand during which months the markets open up to arbitrage opportunities.

Seasonal adjustment methods have a bit of a history, as they were initially developed in the 1920s and 1930s in an empirical way, with the use of non-parametric tools. Parametric models began to be used in the 1950s, and the following development of computer software brought to an enormous growth in this field. There exist, indeed, two categories of seasonal adjustment procedures:

non-parametric methods based on linear smoothing filters, and parametric ones where unobserved components are explicitly specified and estimated. From these two categories, a new one has arisen: that of semi-parametric mixing approaches.

The mother method of Census X-11 was initially developed by Julius Shiskin in 1954 for the US Bureau of the Census, and it was named Method I (Shiskin, 1957; Shiskin, 1978). Following, the researchers proposed eleven experimental versions of Method II, named X-0, X-1, *et cetera*, until the X-11 version of 1965. This version was inspired from moving average smoothing techniques and represented one of the first automatic approaches to seasonal adjustment. X-11 rapidly became a worldwide reference. The method is based on both symmetric and asymmetric weighted moving averages, and it was mostly developed on an empirical basis. X-11 identifies and deletes working days effects, although the integration of holiday effects is not authorized. In this method, the estimates of the trend and of the seasonal components are obtained through a cascade filtering, resulting from the union of different linear filters:

- A 12-term centered moving average;
- Two $3\ x\ (2n+1)$ seasonal moving averages;
- The Henderson moving average.

All of these are defined in Appendix 2. This computation relies on the assumption that the seasonally adjusted time series is equal to a linear trend cycle, plus a random irregular: $Y_t = c_0 + c_1 t + \varepsilon_t$ with $\varepsilon_t \sim IID(0, \sigma^2)$. The equation is:

$$E\left[r_t^{i,m}\right]^2 = c_1^2 (t - \sum_{j=-i}^{m} h_{ij}(t-j))^2 + \sigma^2 \sum_{j=-m}^{m} \left(h_{mj} - h_{ij}\right)^2$$

Where h_{mj} and h_{ij} are the weights of the symmetric and asymmetric filters, respectively (Eurostat, 2018).

The US Bureau of the Census today offers an X-13ARIMA-SEATS model for seasonal adjustment. This software offers a different approach to seasonal adjustment, based on the generation of ARIMA models and on the use of the SEATS software (Gómez and Maravall, 1997). Nonetheless, while this model is considered to be semi-parametric, the X-11 method is non-parametric (or implicit). There is apparently no clear conclusion on which method outperforms the other, systematically (Eurostat, 2018).

The seasonal adjustment is performed on MatLab, thanks to the X-13 Toolbox for Seasonal Filtering by Yvan Lengwiler. The used version, 1.51.1, was last updated on October 23rd, 2021. This toolbox is a "*shell for interacting with the programs of the US Census Bureau, […] that perform seasonal filtering*", states Lengwiler. Thanks to this toolbox it is possible to perform different types of seasonal filtering, among which the X-11 method.

4. EMPIRICAL RESULTS: EQUITY CARRY TRADES OPPORTUNITIES

This paper aims at proving the existence and possibility for seasonal Equity Carry Trades, thus different approaches to address seasonality are used. First and foremost, conventional parametric and non-parametric tests are applied, followed by a linear regression estimation, and finally, the time series will be studied as non-linear, by using the Census X-11 program for seasonal filtering.

4.1. PARAMETRIC AND NON-PARAMETRIC TESTS

ANOVA, Kruskal Wallis, and Levene's tests have been applied on the data. The first Analysis of Variance, also known as the ANOVA test, has not allowed for the rejection of the null hypothesis of equality of means, displaying therefore no seasonality for each dataset. On the other hand, the Kruskal Wallis non-parametric test for equality of means, has yielded different results. While net equity flows continue to present equality of means, stock return differentials present negative seasonality in January, and positive in December. Exchange rate returns present strong positive seasonality in April, and a slightly negative one in May.

These results are not strictly consistent with those obtained with the linear approach, through an Ordinary Least Squares Regression. The latter regression, indeed, displays seasonality in February, April and December for stock return differentials, in January for exchange rate returns, and no sign of seasonality is found for net equity flows. The results of the OLS regression are found in Table 6. Nonetheless, a deeper analysis is conducted; in order to understand the seasonality present in stock return differentials, a regression is conducted on both the S&P 500 and the FTSE 100 returns, separately. These regressions do not explain the seasonality observed in February and April, but FTSE 100 returns show seasonality in December, justifying that of stock return differentials. Exchange rate returns are now analyzed without taking logs: the regression, this time, displays seasonality in April, consistently with the results of the Kruskal

Wallis test. Both the regressions for exchange rate returns, and for stock return differentials are found in Appendix 1, Table A 1. Finally, net equity flows are addressed accounting for breaks: not only the 2008 one found through break tests (that for simplicity purposes was moved to 2009), but also a break in 2000 is taken into account. Results of this regression are shown in Table 7. At this point some seasonality for net equity flows is observed: in the period that goes from January 1986 to December 1999, seasonality is present in June, October and November, while it is present in March for the period January 2010 – December 2019.

4.2. SEASONAL FACTORING WITH CENSUS X-11

Until now, results only partly match the expectations of this paper, as some January effect is found in the stock market through the Kruskal Wallis test of equality of means, and it is found for the foreign exchange market in the OLS regression. Nonetheless similarities between the two markets cannot be found, as the different analyses are not comparable. At this point it is possible to state that some seasonal behavior does exist in the considered datasets. Thus, since

Dependent Variables	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
ΔLFTSE100 - ΔLS&P500	-0.008	*0.012	-0.001	*0.012	0.000	-0.001	0.009	0.009	0.004	0.005	-0.002	**0.016
p-Values	0.106	0.077	0.845	0.094	0.962	0.937	0.182	0.193	0.531	0.475	0.817	0.018
ΔL(GBP-USD)	***0.204	-0.002	-0.002	0.003	-0.001	-0.001	0.001	-0.002	0.000	0.000	-0.001	0.001
p-Values	0.000	0.845	0.870	0.818	0.910	0.950	0.922	0.882	0.969	0.976	0.924	0.937
NEF	-0.006	-0.010	0.011	0.007	0.010	0.014	0.013	-0.006	0.005	0.012	0.012	0.012
p-Values	0.367	0.297	0.213	0.423	0.277	0.116	0.156	0.506	0.588	0.194	0.179	0.203

Table 6 - Linear model estimation for stock return differentials, exchange rate returns, net equity flows.

**** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level*
ΔLFTSE100 - ΔLS&P500 represents stock return differentials between the British FTSE 100 and the American S&P 500 indices. ΔL(GBP-USD) is the GBP/USD exchange rate return, and NEF stands for Net Equity Flows from the US to the UK.
The rows p-Values contain the p-Values for the coefficients of the corresponding above line.
Sample: January 1986 to December 2019 for all time series.

Dependent Variables	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
NEF 2010-2019	0.003	-0.001	**0.015	0.001	0.009	-0.003	0.001	-0.003	-0.007	-0.002	-0.003	0.001
p-Values	0.584	0.865	0.025	0.923	0.192	0.623	0.897	0.621	0.317	0.775	0.685	0.820
NEF 2000-2009	-0.008	-0.023	0.001	0.007	0.012	0.009	0.014	-0.027	0.002	0.007	-0.001	0.003
p-Values	0.590	0.242	0.955	0.727	0.535	0.653	0.485	0.181	0.932	0.742	0.954	0.886
NEF 1986-1999	-0.012	-0.004	0.018	0.014	0.010	**0.032	0.022	0.008	0.017	*0.027	**0.034	0.026
p-Values	0.291	0.787	0.275	0.397	0.515	0.047	0.168	0.618	0.298	0.097	0.036	0.101

Table 7 - OLS Regression on Net Equity Flows with breaks in 2000 and 2009

**** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level*
NEF stands for Net Equity Flows from the US to the UK.
The rows p-Values contain the p-Values for the coefficients of the corresponding above line.
The considered time spans are January 2010 to December 2019 in the first two rows, January 2000 to December 2009 in the third and fourth rows, and January 1986 to December 1999 in the fifth and sixth rows.

seasonality can be directly observed by using a seasonal factoring algorithm, such an algorithm, the Census X-11, will be used here to extract the seasonal components of each time series.

4.2.1. FOREIGN EXCHANGE MARKET

By applying the Census X-11 algorithm to the dataset of exchange rate returns, it is possible to obtain the seasonal component for each month throughout the given time span (January 1986 – December 2019). Positive seasonality is mostly observed in April, where it is quite strong, while negative seasonality can be seen for May and August. The April result is consistent both with the OLS regression result on exchange rate returns, without logs, and with the Kruskal Wallis test. The idea here, would be to sell the pound and buy the dollar in May and August, while in April one should short the dollar and take a long position on the pound. In order to understand whether these months pave the way to some arbitrage opportunity, it is necessary to compare these figures to those of stock return differentials. Figure 7 represents the seasonal factors of the foreign exchange returns dataset. Seasonality can be observed in each month, as the time series

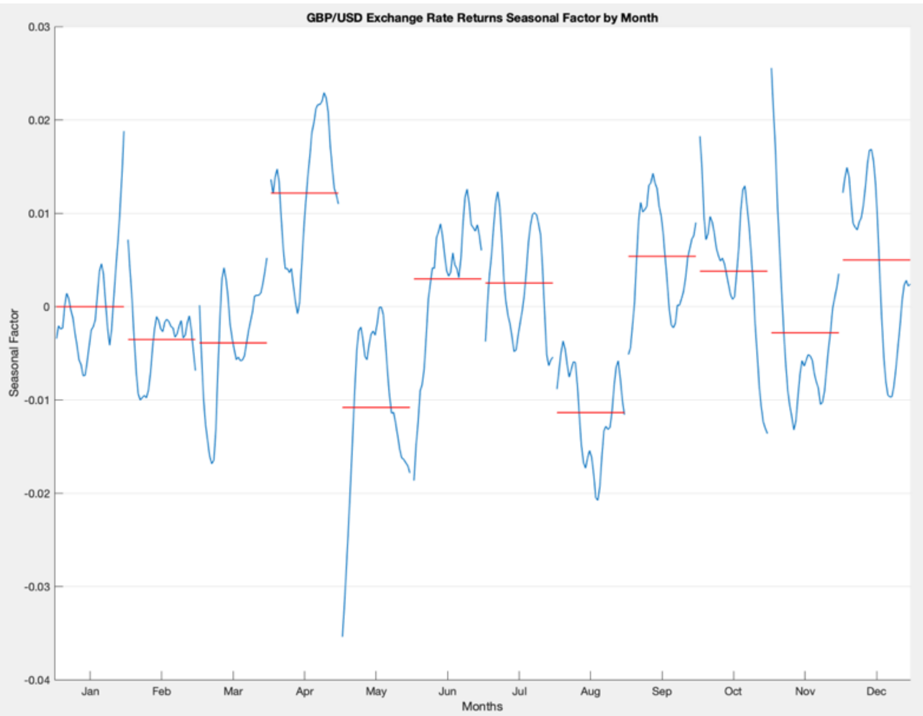


Figure 7 - GBP/USD Exchange Rate Returns Seasonal Factor representation by month.

The blue lines represent the behavior of the seasonal factor in each month, for the time period that goes from January 1986 to December 2019. The red lines represent the mean for each monthly group of seasonal factors.

presents a quite irregular behavior. According to Reuters market analyst Martin Miller, one cause for the constantly increasing exchange rate returns in the month of April is the international inflows at the beginning of UK's financial year, which lead to a strong demand for the pound (Nasdaq, 2022).

4.2.2. STOCK MARKETS

In this paragraph, stock return differentials are studied in terms of their seasonal movements. Figure 8 shows the behavior of the seasonal factors, and their monthly means: it can be easily noticed that there exists a strong seasonal behavior both in January (negative), and in December (positive). The latter is consistent with what was found in the OLS analysis. Each month displays some seasonality, although less intense than that of January and December, but it can be noticed that both February and April, which yielded a positive seasonal behavior in the OLS regression, are again positively positioned. It is also interesting to observe the seasonal factors of the returns of the S&P 500 and the FTSE 100, separately, in order to understand, once again, if the individual stock

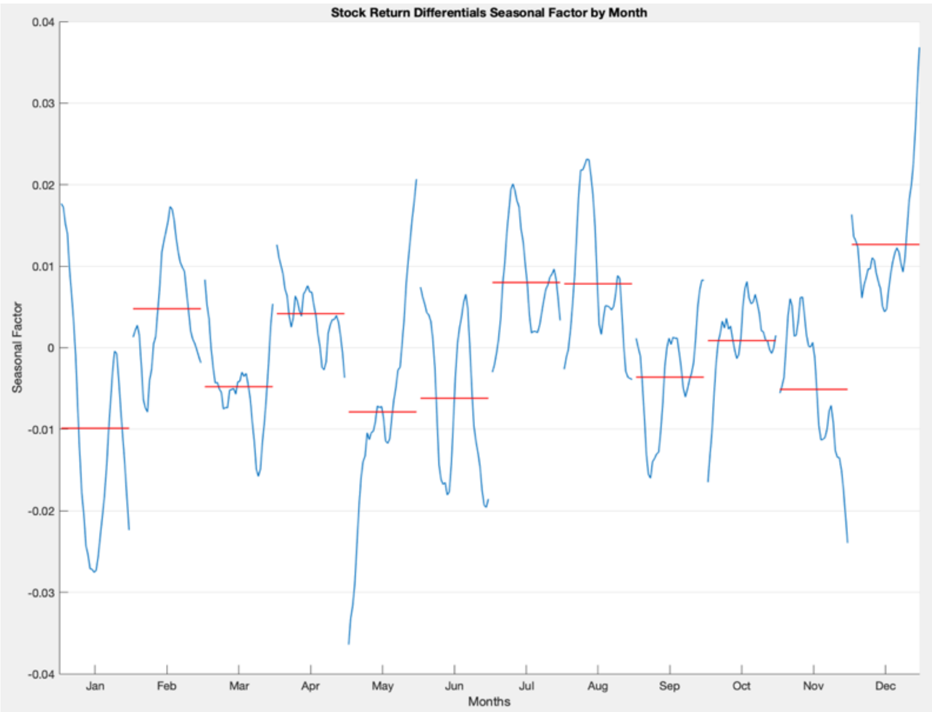


Figure 8 - Stock Return Differentials, FTSE100 - S&P500, Seasonal Factor representation by month.

The blue lines represent the behavior of the seasonal factor in each month, for the time period that goes from January 1986 to December 2019. The red lines represent the mean for each monthly group of seasonal factors.

markets influence at all the seasonality in the stock return differentials. The graphical representations of the seasonal factors of the S&P 500 and the FTSE 100 indices, which can be found in Appendix 1 (Figures A 6 and A 7), imply that, while the FTSE 100 index does not show any seasonality for the month of January, the S&P 500 displays positive seasonality for that month. On the other hand, the December effect is partly explained by the behavior of the S&P 500 returns, and abundantly explained by the FTSE 100 returns.

There are numerous explanations to the occurrence of the positive January effect in the American stock market: for example, Gultekin and Gultekin (1983) analyze the causality between the seasonal effect and the turn of the tax year. Indeed, in the literature, the turn of the year effect is often explained through tax-loss selling at the end of the tax year (Roll, 1983). On the other hand, Chen (2012) argues that Januaries present higher levels of volatility than other months, and this might explain the excess returns that some equity markets show in such a month. Another view on what causes seasonality in January is window dressing (Haugen and Lakonishok, 1988; Lakonishok *et al.*, 1991) which refers to fund managers who sell shares at the end of the year that have performed poorly, in order to buy them back at the beginning of the new year. Transaction costs explain why returns in January are much lower for low-price stocks rather than high-price ones (Bhardwaj and Brooks, 1992), while other explanations rest on liquidity (Ogden, 1990), the business cycle (Kohers and Kohli, 1992), and microstructure factors (Draper and Paudyal, 1997).

4.2.3. COMPARISON: A MARCH EFFECT?

Finally, in order to achieve the purposes of this paper, it is necessary to compare stock return differentials with the foreign exchange returns. By looking at Figure 9, similarities in monthly behavior are hardly observable: in the negative part of the graph, the only comparable months are March and November, as they both have a value between 0.00 and -0.01 for both datasets. Nonetheless, such values are not identical between the two time series. No similar situation can be observed in the positive months. March has a mean value of -0.0039 for exchange rate returns, and a value of -0.0048 in stock return differentials.

The fact that return differentials, computed as FTSE100 – S&P500 have negative seasonality in March, means that during that month the British market is performing worse than the American one. According to Equity Carry Trades, investors should abandon the low performing British market to move to the better performing American one. This behavior is indeed confirmed by the depreciation of the British pound in March, which presents a very similar seasonality to that of stock return differentials.

On the other hand, in foreign exchange returns, considerable seasonality is observed in April, May and August. In the cases of April and May, stock return differentials move in the same direction as the exchange rate, opening up some arbitrage opportunity, although the movement is of a different amount and is thus not strictly comparable. In the case of August, stock markets behave differently than the forex market, thus there is certainly no room for Equity Carry Trades. Meanwhile, in the stock market differentials, seasonality is present in January and December, although this seasonality does not seem to have been arbitraged

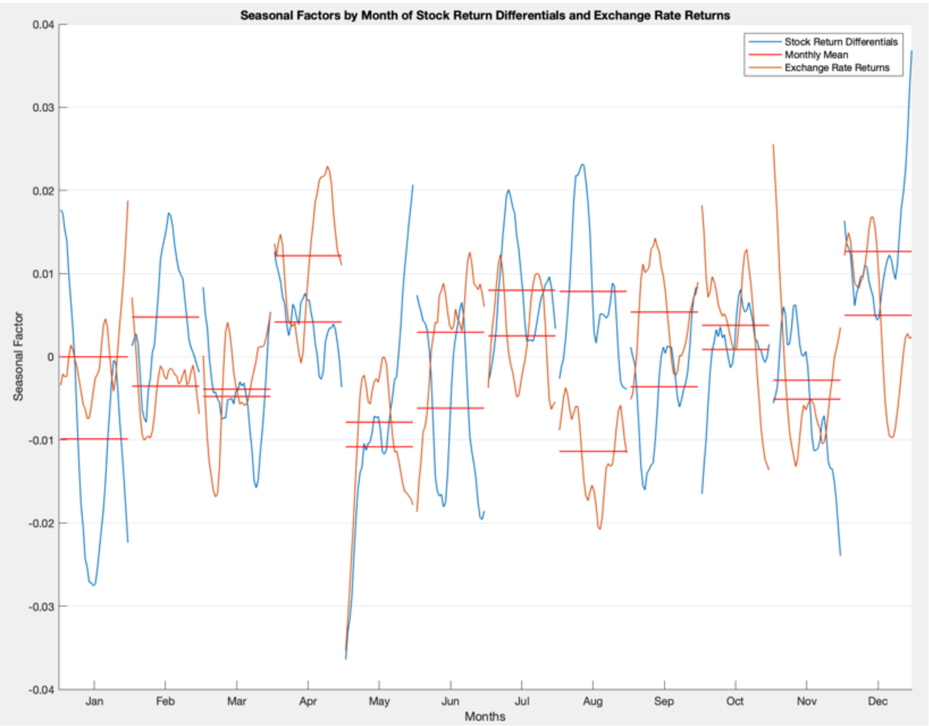


Figure 9 - GBP/USD Returns and Stock Return Differentials Seasonal Factors.

The blue line represents the seasonal component of the ΔLFTSE100 – ΔLS&P 500, by month.
The orange line represents the seasonal component of the GBP/USD exchange rate returns, by month.
The red lines represent the average seasonal factor for each month, for each dataset.

away through Equity Carry Trades, since the exchange rate does not vary accordingly. December, much as previously seen April and May, in the exchange rate at least presents seasonality in the same direction as the stock markets, although with a lower amount. Standard non-arbitrage theory generally allows for the sign of the correlation between equity returns and forex returns to be positive, negative, or zero. Nonetheless, what is observed in the market is somehow different: there is indeed not much literature on the empirical correlation between the two sets of returns (Cenedese *et al.*, 2015).

In Appendix 1 (Figures A 8, A 9, A 10) it is possible to find a similar analysis on the two datasets (stock return differentials and exchange rate returns) that takes into account shorter periods. In this case the datasets are respectively split in three parts by decade (from January 1986 until December 1997, from January 1998 to December 2008, and from January 2009 to December 2019), and the seasonal factor is extracted from each part. This research aims at understanding whether the Census X-11 detects different seasonal behaviors if it deals with a different span of time, and at analyzing in which periods the seasonal behavior was most active. Nevertheless, this analysis does not yield very interesting results for this research, besides a strong April effect in the 2009-2019 decade for the foreign exchange returns.

Finally, Figure 10 represents the movements over time of the seasonal components of the stock return differentials, the exchange rate returns, and the net equity flows. When observing these movements, it is interesting to notice how they vary over time. Let’s consider the most important historical example: the Global Financial Crisis. It can be noticed that stock return differentials experience an increase in seasonality in the years surrounding the crisis: negative seasonality is quite prominent in the years that go from 2000 to 2006, while from 2007 until 2012 seasonality is mostly positive, and it returns to the negative side in the following years. Around 1995, on the other hand, seasonality is very modest. This may be connected to the Small Banks’ Crisis of the early 1990s that occurred in the UK: in that matter, the Bank of England provided emergency liquidity support to British banks, perhaps constraining any abnormal behavior in stock returns (Logan, 2001). The GBP/USD exchange rate returns present a much more stable path of seasonality, with no big alterations over time, with the exception of the last three to four years of the sample, that seem to display a stronger seasonal behavior. A number of events affected the behavior of the currency market in those years: general elections in 2015 in the UK caused volatility, stock market mayhem in China hit commodity and mining stocks, dragging the British stock market down with it, and for the first time after the Global Financial Crisis the Federal Reserve raised interest rates in the United States (HL, 2015). Finally, net equity flows display some interesting movements as well: seasonality seems to be very important at the beginning of the time series, only to gradually soften until reaching very low levels after the Global Financial Crisis.

In Appendix 1 (Figure A 12 to A 15) it is possible to find a similar analysis on stock market indices prices and on foreign exchange rates, alongside net equity flows, performed not with the Census X-11 method, but with the CAMPLET algorithm

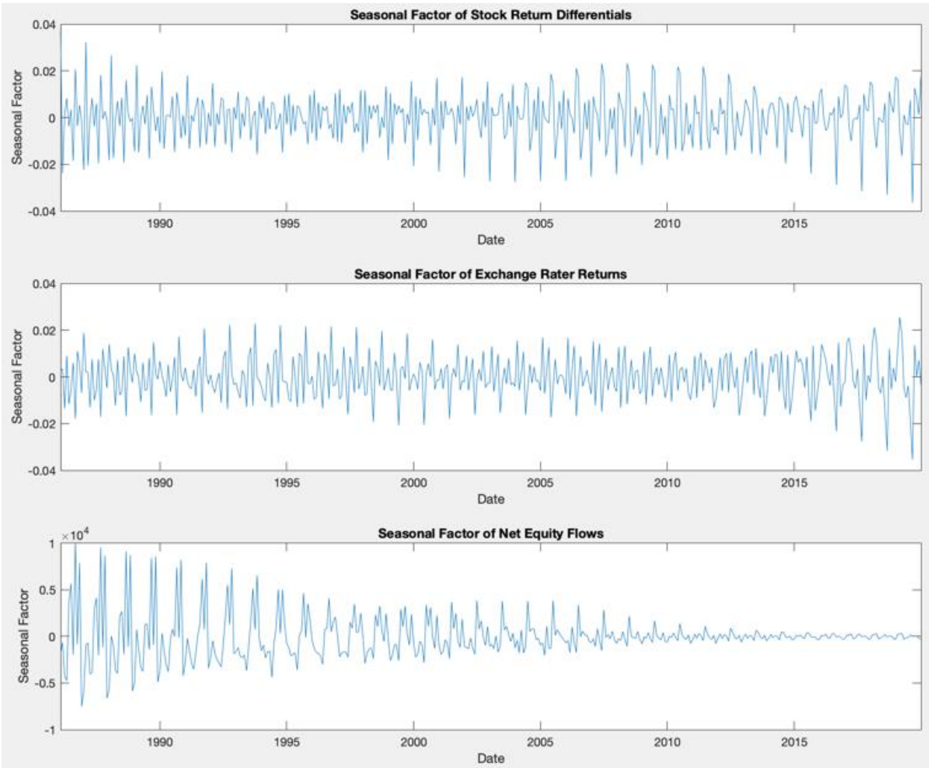


Figure 10 - Seasonal components over time.

In the first panel the seasonal component of the stock return differentials ΔLFTSE100 – ΔLS&P 500 is displayed.
In the second panel the seasonal component of the exchange rate returns GBP/USD is shown.
In the third panel the seasonal component of the net equity flows from the US to the UK is displayed.
The considered time span is January 1986 – December 2019.

(Abeln and Jacobs, 2015). In the same way, the analysis performed while taking into account the results of the break tests, can be found in the same Appendix (Figures A 16 to A 19). Prices display less seasonal behaviors than returns, but it can be observed that both UK and US prices move similarly over the year. March presents proportionally higher prices for the S&P 500 than for the FTSE 100, consistently with what was found for stock return differentials. Nevertheless, the GBP/USD exchange rate displays positive seasonality in such month, suggesting an appreciation of the pound with respect to the dollar. However, prices represent an absolute measure, rather than a relative one. Returns, indeed, allow the study of seasonality to account for the other months of the year, rather than an individual one.

The profit opportunities that would arise from exploiting the seasonality that has just been observed need to take into account the transaction costs. It is important to make sure that transaction costs, most commonly the bid-ask spread for the foreign exchange market, do not exceed the profits arising from the arbitrage transaction. Such profits, accounting for transaction costs, can be found in Appendix 1, Table A 2. The bid-ask spread is available in its variations on Datastream since 2012 only, thus, for the previous years, a fixed average (of the data between 2012 and 2019) of 4 pips is taken. What is observed in Table A 2 is that, regardless of the spread being variable or fixed, all arbitraging transactions taking place in the foreign exchange market in the month of March are profitable net of the spread.

4.2.4. NET EQUITY FLOWS AND SEASONAL CARRY TRADES

This paragraph will address the behavior of net equity flows, in order to understand whether the observations obtained from the analysis of stock market return differentials and exchange rate returns are consistent with what is observed for capital flows. What is looked for here is a confirmation that investors do abandon the British market to move to the American one in March, and a view on how they behave in January and December, since it was observed that considerable seasonality is present in those months as well for returns on both equity and foreign exchange markets.

The analysis begins by understanding what is the best way to address seasonal behavior in net equity flows: Figure 11 displays a comparison between a Census X-11 analysis on the whole time series (in blue) versus the same analysis performed on two sub-samples: from January 1986 until August 2008, as the break test suggests, and from September 2008 until December 2019 (red). The two panels in the figure respectively represent the seasonally adjusted time series, and the seasonal component. When separately studying the two sub-periods of the time series, it is possible to observe a more mitigated seasonal behavior, than what is observed with the whole period's analysis. In order to confirm this, Figure 12 compares the original data on net equity flows with the seasonally adjusted time series, computed for the full sample in the first panel, and the two sub-samples in the second one. What can be noticed in both figures is that there is a difference in the seasonal adjustment, according to the type of analysis that was performed. In general, a study by parts, yields results that resemble more closely the behavior of the original time series, making the

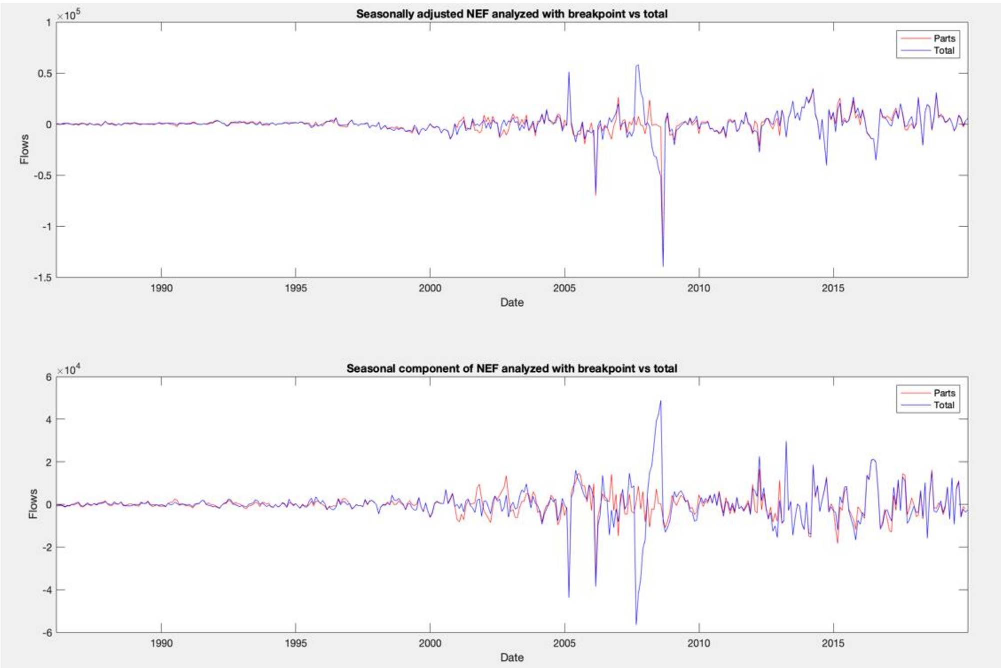


Figure 11 - Seasonal Adjustment of Net Equity Flows

The blue line represents the seasonal adjustment of the time series as a whole: form January 1986 until December 2019.
The red line represents the same seasonal adjustment, performed on the time periods January 1986-August 2008 and September 2008-December 2019 separately, according to the results of the break test.
The first panel displays the seasonally adjusted time series, while the second panel displays the seasonal components.

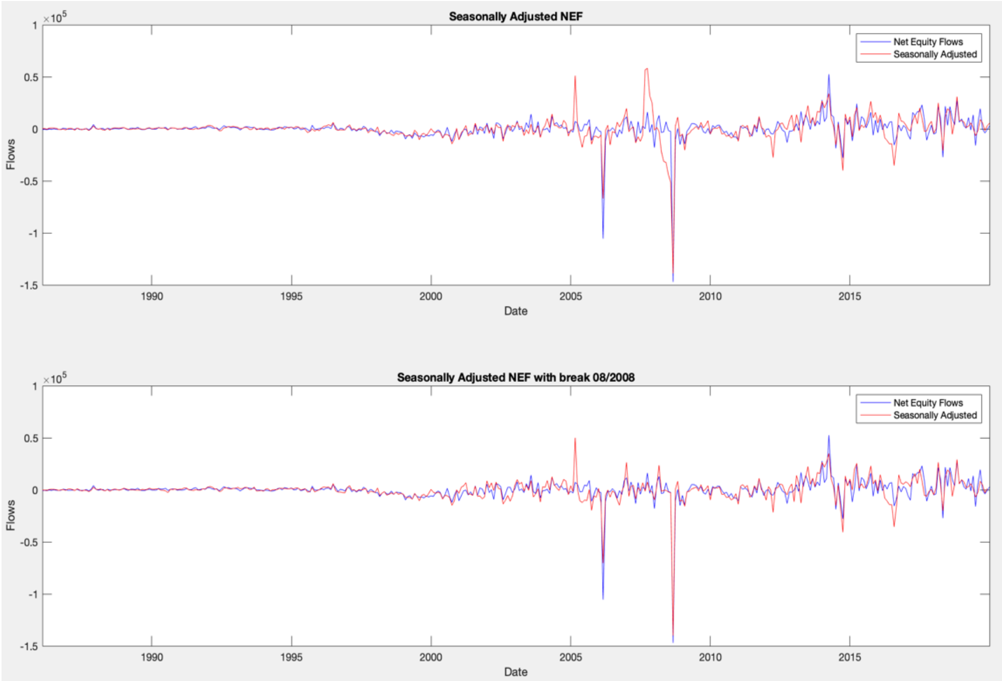


Figure 12 - Seasonal Adjustment of Net Equity Flows

The blue line represents the original net equity flows time series, from January 1986 until December 2019.
The red line represents the seasonal adjustment.
The first panel compares the seasonally adjusted time series as a whole with the original one.
In the second panel the seasonal adjustment is performed on the time periods January 1986-August 2008 and September 2008-December 2019 separately, according to the results of the break test.

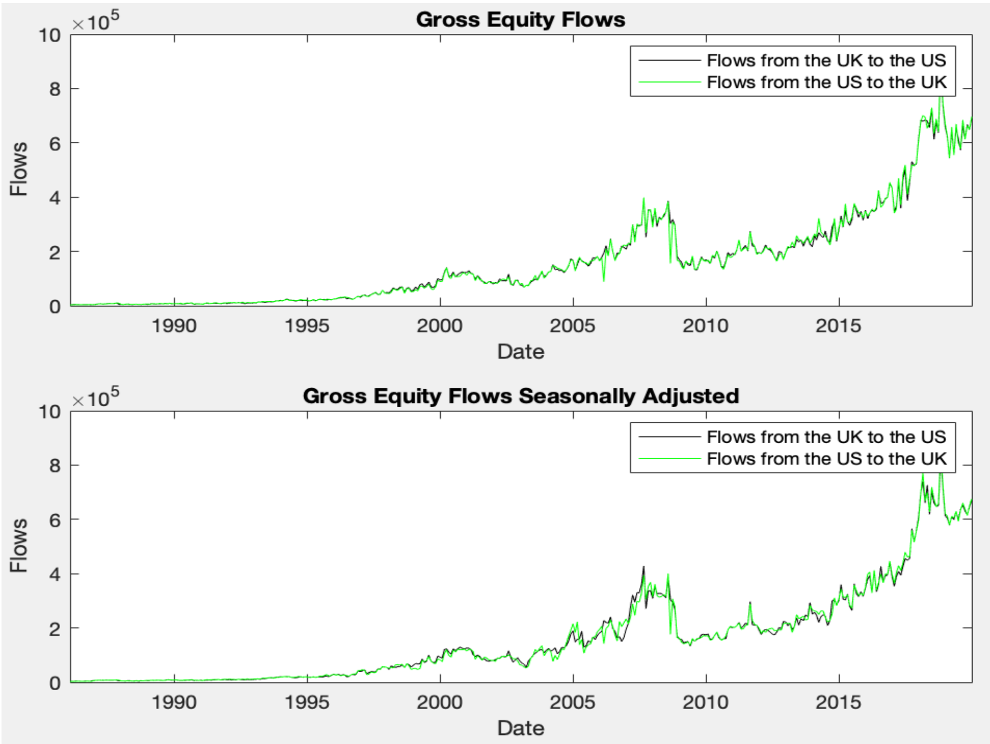


Figure 13 - Gross equity flows between the UK and the US.

The black line represents gross flows from the UK to the US.
The green line represents gross flows from the US to the UK.
In the first panel the two raw time series are compared (non-seasonally adjusted), while in the second panel the seasonally adjusted time series are compared.

seasonal adjustment seemingly more accurate in such case. One peculiarity of this analysis is that it seems that the algorithm is dependent on the starting value.

A third graphical analysis of this time series deals with the seasonal adjustment of the gross equity flows in each direction. Figure 13 compares the raw flows in both directions in the first panel, and the seasonally adjusted flows in the second one. It is interesting to observe how the flows behave similarly between the two countries, regardless of the direction, probably due to the high correlation between the two markets. Besides, while the United States are the foremost destination for many international investors, given their highly liquid, developed and efficient financial markets, London has been a major financial center since the 19th century, leading Europe in financial services investments, and the world in foreign exchange trading (City of London, 2022). As the two economies have increasingly expanded, the Global Financial Crisis hit both countries in the late 2000s.

Going back to the Ordinary Least Squares regression, performed in Section 4.1, it was observed that net equity flows present different seasonal behaviors according to the considered time period (Table 7). Besides June, October and November are significant in the time span that goes from January 1986 until December 1999, and March turned out to be significant between January 2010 and December 2019. These results are not necessarily consistent with those of the other time series (February, April and December for stock market returns, and in January and April for the GBP/USD exchange rate, Table 6); nonetheless, it is interesting to keep in mind the significance of seasonality in March, given previous observations from paragraph 4.2.3.

Finally, it is important to understand whether the Equity Carry Trade opportunities that were observed in the comparison between stock return differentials and exchange rate returns are exploited by investors, by studying the behavior of net equity flows. Net equity flows are taken into consideration as moving from the United States to the United Kingdom. When observing their seasonal behavior, a movement from the UK to the US in March would be expected, since the American market is better performing, and the dollar is appreciating.

Nonetheless, this is not what is observed here: the positive movement of the March seasonal component seen in Figure 14, indicates a dominance of equity flows from the US to the UK rather than the opposite. This can be explained by the presence of other types of flows that occur in the market and that may influence equity ones: cash, bonds or other financial instruments, bank or mutual fund flows, *et cetera*. Furthermore, flows between the UK and the US may transit via some offshore centers or tax havens, such as the Cayman Islands, or Bermuda (Coppola *et al.*, 2019). By moving on to observe January and December, in order to explain at least partly the previous findings in the stock markets, it is possible to see how, while December, like March, displays a behavior that is contradictory with expectations, January does not. January earlier presented negative returns in the stock markets, implying the existence for an opportunity to drop off the British market and enter the American one to enhance profits. This behavior would be accompanied by a depreciation of the British pound, which although is not observed here. Nonetheless, net equity flows are consistent with the Equity Carry Trade assumption, since their seasonality is present in the UK-to-US direction, as expected.

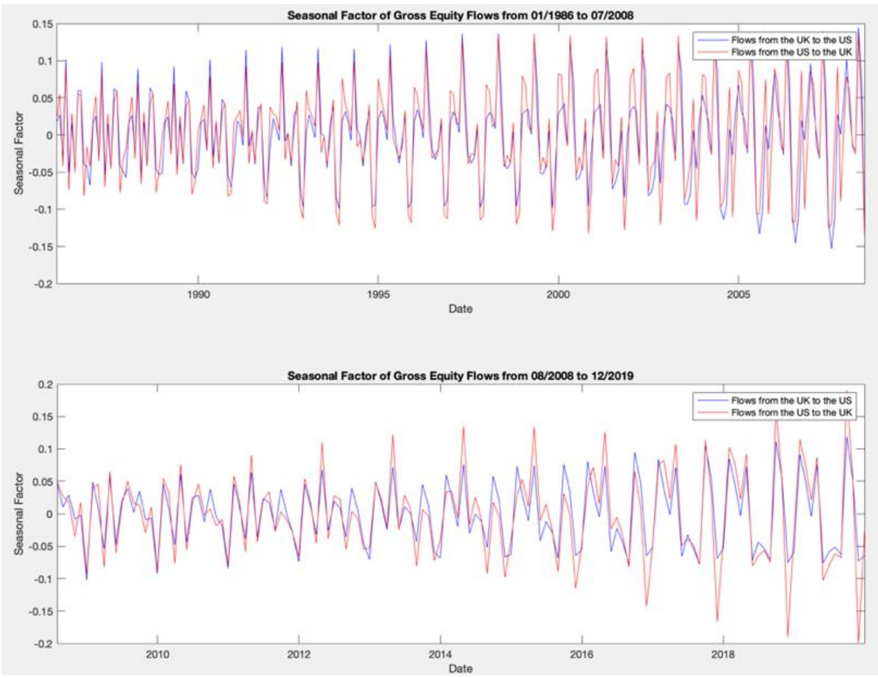


Figure 14 - Net Equity Flows Seasonal Factor representation by month.

The blue lines represent the behavior of the seasonal factor in each month, for the time period that goes from January 1986 to December 2019.
The red lines represent the mean for each monthly group of seasonal factors.
Net equity flows are obtained from gross flows from the US to the UK – gross flows from the UK to the US.

The analysis of monthly seasonal factors dividing the time series by decades (as it was done for stock return differentials and exchange rate returns) can be found in Appendix 1 (Figure A 11) for net equity flows as well. In the case of net equity flows, in the third panel of Figure A 11, it can be observed that both February and April behave consistently with what is observed in the graphs of stock return differentials and exchange rate returns (Figure A 8). February, between 1986 and 1997, displayed flows from the UK to the US, while the American market was performing better than the British one and the dollar was appreciating. On the other hand, during April, flows went mostly from the US to the UK, while the British market was performing well and the pound was appreciating.

On a side note, the behavior of the seasonal factor of gross equity flows between the two countries is analyzed, by dividing the time series according to the results of the break tests, in August 2008. It is interesting to observe, in Figure 15, how the two time series behave similarly, implying a correlation in the movement of capital flows between the two countries. As previously mentioned, the two countries are strongly correlated in history and economic dynamics; besides, the

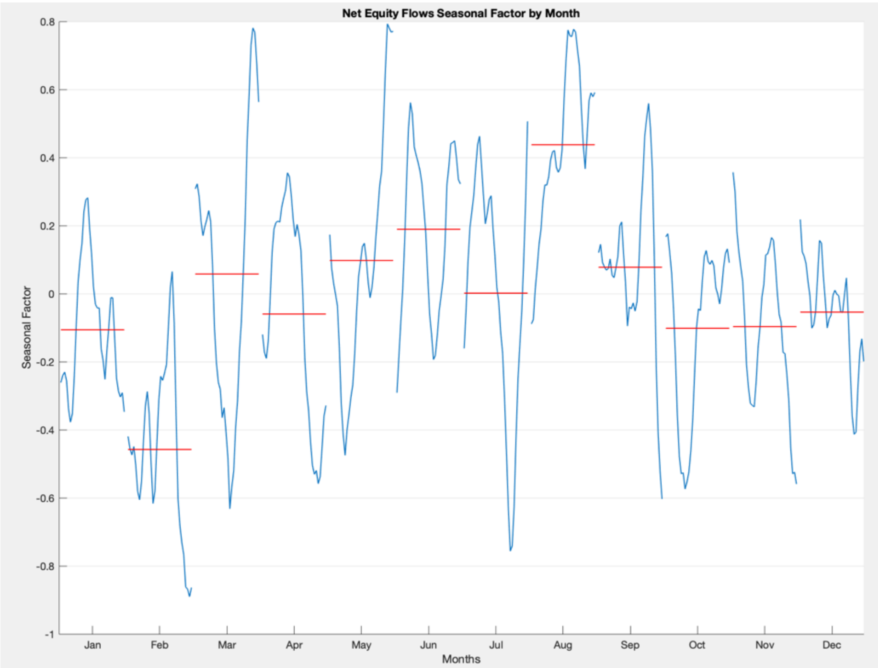


Figure 15 - Seasonal Factors of Gross Equity Flows, between the US and the UK.

The time series is seasonally adjusted.
The blue line represents gross flows from the UK to the US, while the red line represents gross flows from the US to the UK.
The first panel compares the two flows from January 1986 to July 2008, and from August 2008 until December 2019, separately.

fact that international capital flows are often studied in terms of US variables, such as the VIX or Federal Reserve's monetary policies, cannot be neglected. On this issue McQuade and Schmitz (2019) have provided a thorough analysis. The two scholars suggest, indeed, that variations in US variables have an important impact on global financial flows, and that the neglect of global indicators will soon not be adequate anymore, as other regions, such as China or the euro area, are becoming increasingly important at the global level. This is mentioned to understand how a cross-border spillover effect is in fact in place and makes the observed behavior of gross equity flows much less unexpected than it would seem to be.

5. CONCLUSIONS

This dissertation analyzed the behavior of the American and British stock markets and that of their currencies, in order to understand whether there exists the possibility to engage in Equity Carry Trades, by exploiting the seasonal behavior of the exchange rate returns of the GBP/USD currency pair, and the profit opportunities that arise from seasonality in the corresponding stock markets. This has been studied by accounting for net equity flows between the two countries, for which they represent the engine of Equity Carry Trades.

After performing a number of parametric and non-parametric tests of seasonality, the research went on to study linearly the time series, and finally to engage in a non-linear approach. The latter approach has been that of extracting the seasonal components of each dataset, thanks to the use of the Census X-11 algorithm, provided by the US Census Bureau. By extracting such seasonal components, it was possible to understand whether certain months presented similar seasonal behavior in the stock markets (analyzed as stock return differentials) and in the foreign currency market. The obtained results, showed that, rather than the most commonly expected January effect, which allegedly affects the United States stock market, this specific scenario allows for Equity Carry Trade opportunities in the month of March. In this month, indeed, the seasonal components of the two time series amount to very similar values: this means that as the British pound depreciates, and the British market underperforms, the arbitrage opportunity is open by buying the US dollar, selling the British pound, and exploiting the superior returns of the American stock market.

Net equity flows have been studied at length as their behavior is often influenced by a large number of external factors, thus it may not be surprising they do not yield a result that is in line with what was found in terms of Equity Carry Trade opportunities. Net equity flows between the US and the UK are indeed influenced by the fact that they are often considered to be driven by US variables, and that a cross-border spillover effect is in place between the two countries.

Literature on Equity Carry Trades is still blooming, and this paper contributed to providing a method to address the phenomenon when one desires to study two countries with different currencies, plus it provides an insight on one of the most important and commonly used currency pair on the market.

APPENDICES

APPENDIX 1

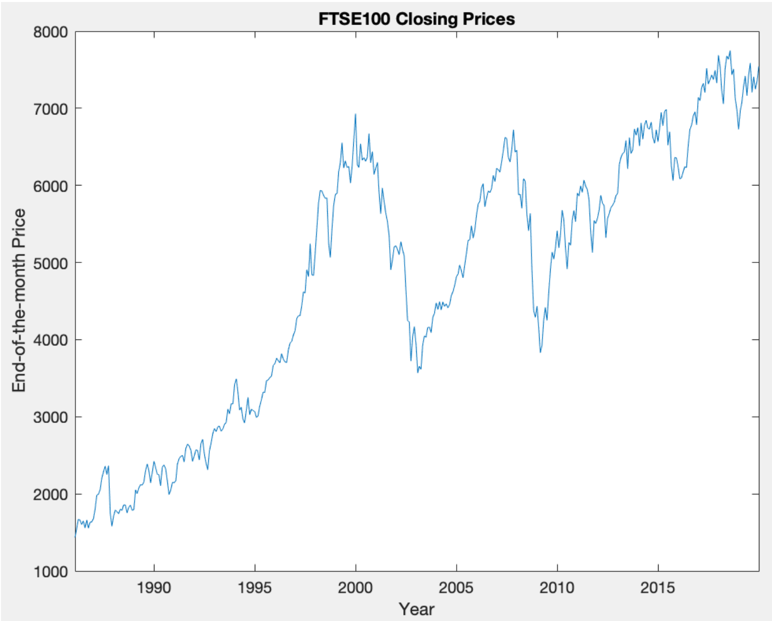


Figure A 1 - FTSE 100 Monthly Closing Prices (1986-2019).

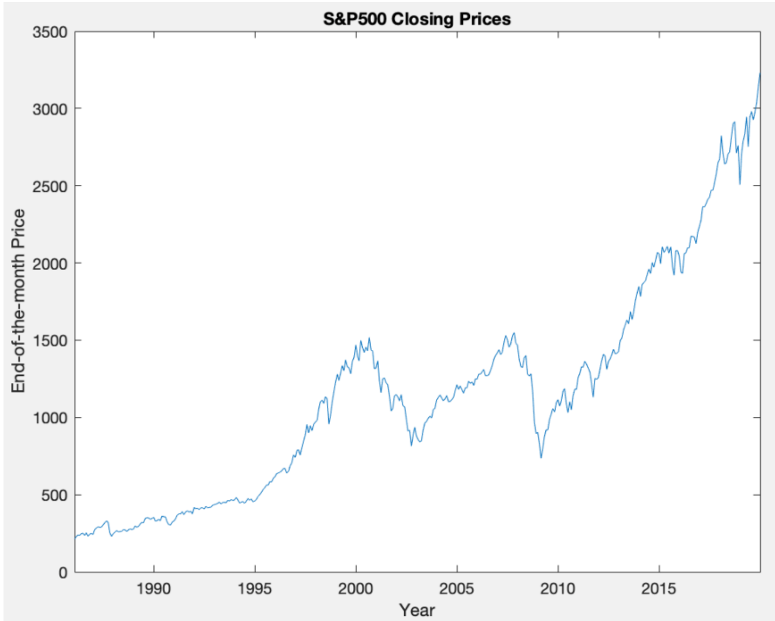


Figure A 2 - S&P 500 Monthly Closing Prices (1986-2019).

Dependent Variables	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
ΔLS&P500	0.010	-0.004	0.003	0.005	0.000	-0.009	0.001	-0.015	-0.015	-0.003	0.002	0.004
p-Values	0.164	0.724	0.752	0.634	0.992	0.384	0.953	0.138	0.150	0.786	0.848	0.695
ΔLFTSE100	0.002	0.009	0.002	0.017	0.000	-0.010	0.010	-0.006	-0.011	0.002	0.000	**0.020
p-Values	0.749	0.408	0.852	0.111	0.967	0.354	0.342	0.533	0.303	0.838	0.970	0.049
Δ(GBP-USD)	-0.004	-0.001	0.005	**0.0153	-0.005	0.006	0.009	-0.002	0.008	0.005	0.003	0.009
p-Values	0.375	0.883	0.414	0.022	0.470	0.366	0.181	0.724	0.251	0.439	0.684	0.166

Table A 1 - OLS Regression on S&p 500 returns, FTSE 100 returns, and non-log exchange rate returns.

*** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level*
ΔLFTSE100 - ΔLS&P500 represents stock return differentials between the British FTSE 100 and the American S&P 500 indices. ΔL(GBP-USD) is the GBP/USD exchange rate return, and NEF stands for Net Equity Flows from the US to the UK.
The rows p-Values contain the p-Values for the coefficients of the corresponding above line.
Sample: January 1986 to December 2019 for all time series.

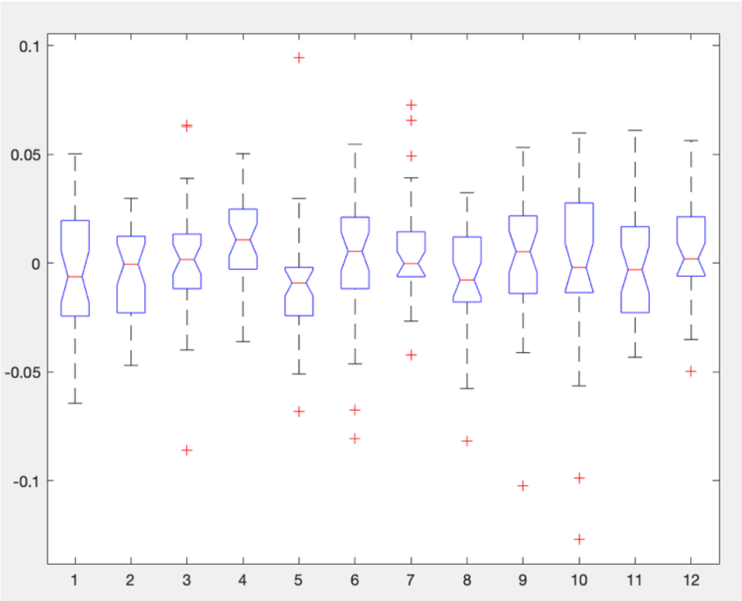


Figure A 3 - Exchange rate returns Kruskal Wallis Test.

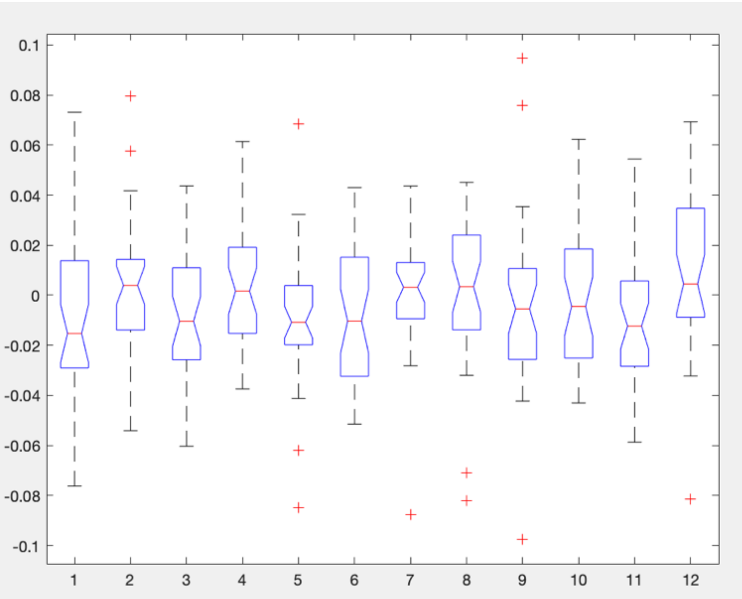


Figure A 4 - Stock return differentials Kruskal Wallis Test.

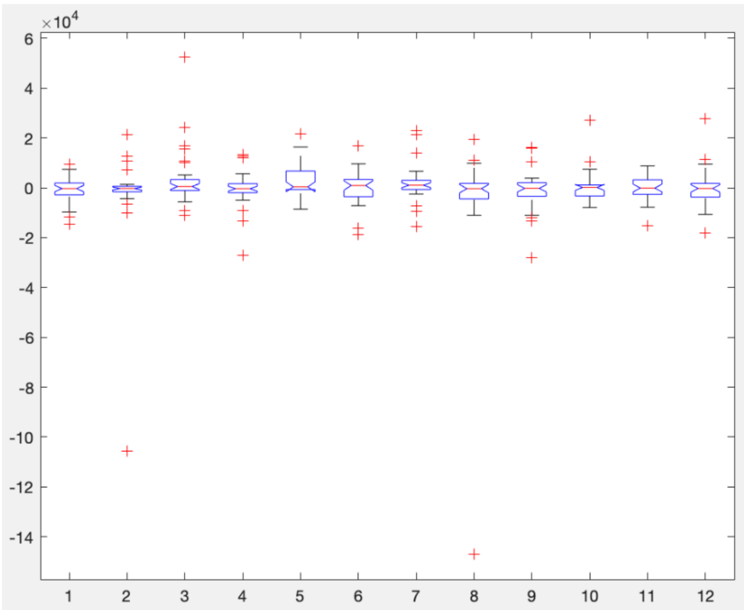


Figure A 5 - Net equity flows Kruskal Wallis Test.

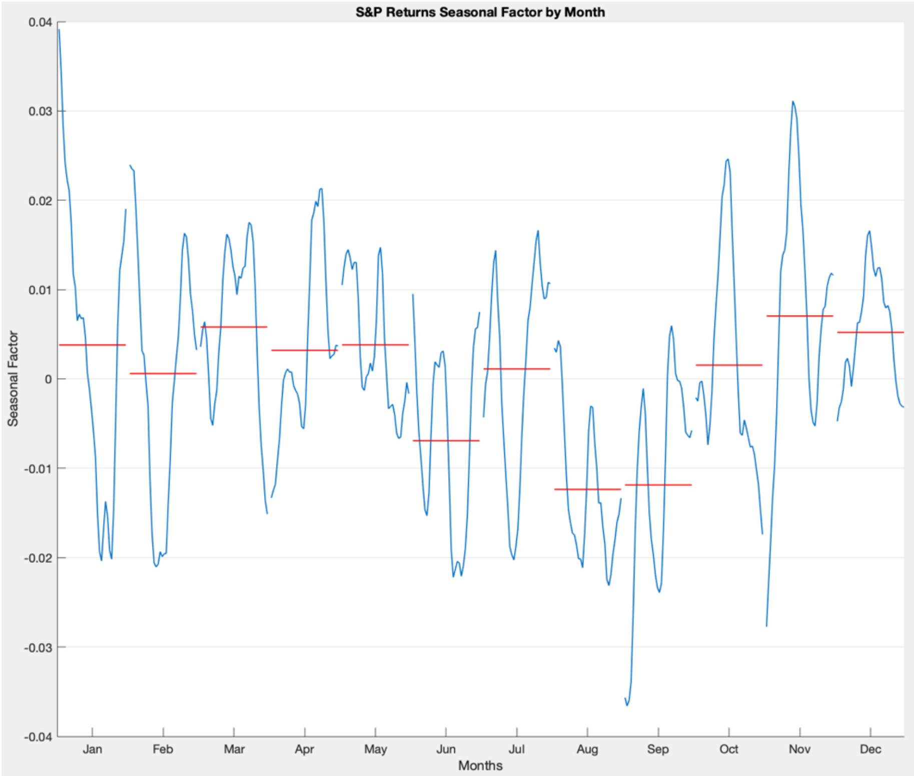


Figure A 6 – S&P 500 Seasonal Factors.

The blue lines represent the behavior of the seasonal factor in each month, for the time period that goes from January 1986 to December 2019. The red lines represent the mean for each monthly group of seasonal factors.

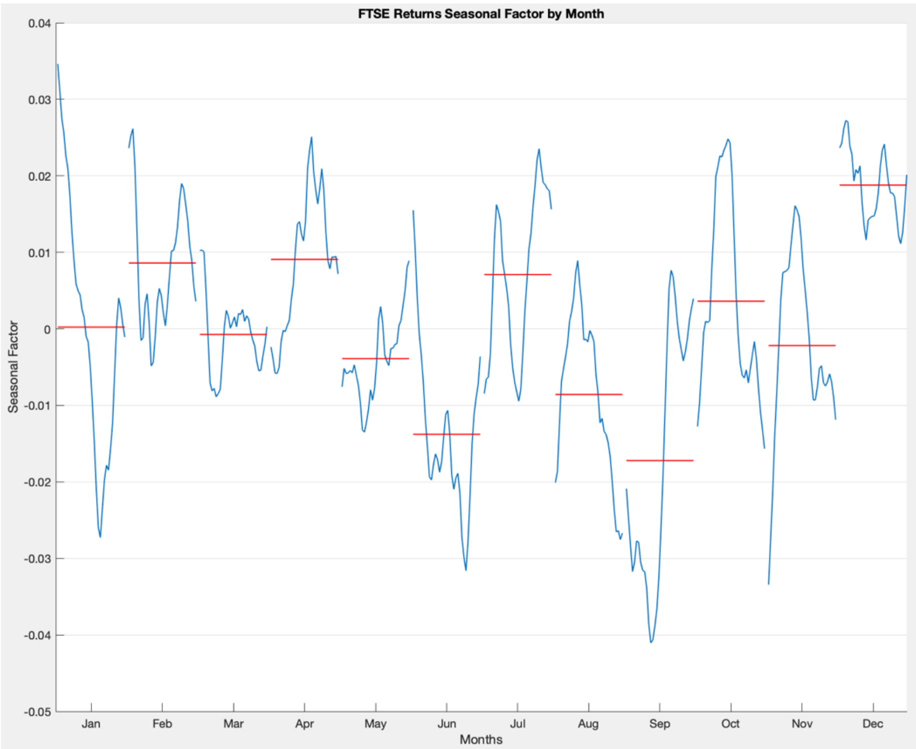


Figure A 7 - FTSE 100 Seasonal Factors.

The blue lines represent the behavior of the seasonal factor in each month, for the time period that goes from January 1986 to December 2019. The red lines represent the mean for each monthly group of seasonal factors.

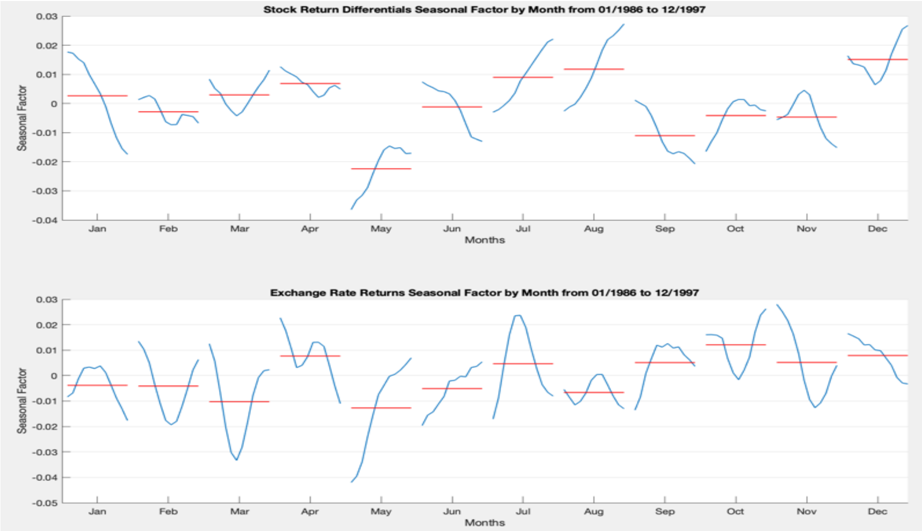


Figure A 8 - Seasonal Factors comparison, from 01/1986 to 12/1997.

Stock return differentials and exchange rate returns.
The blue line represents the behavior of each month's seasonal components, while the red line indicates the monthly average.

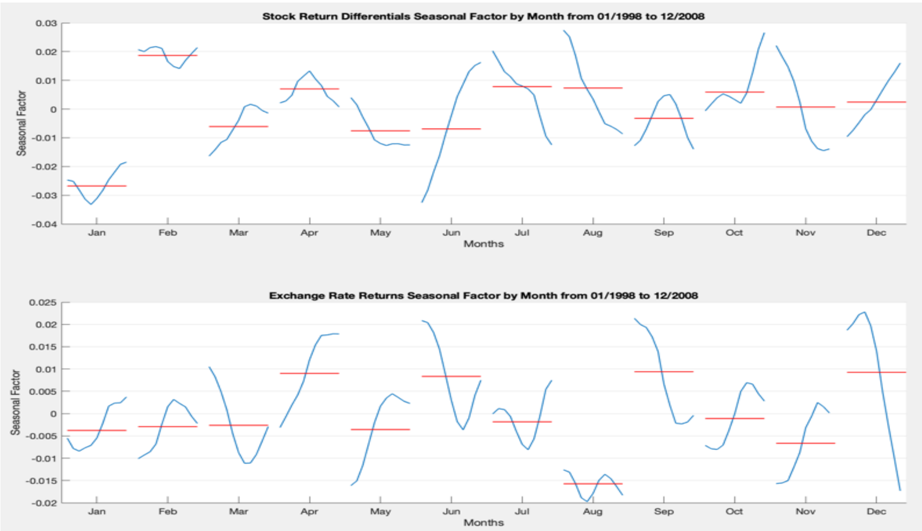


Figure A 9 - Seasonal Factors comparison from 01/1998 to 12/2008.

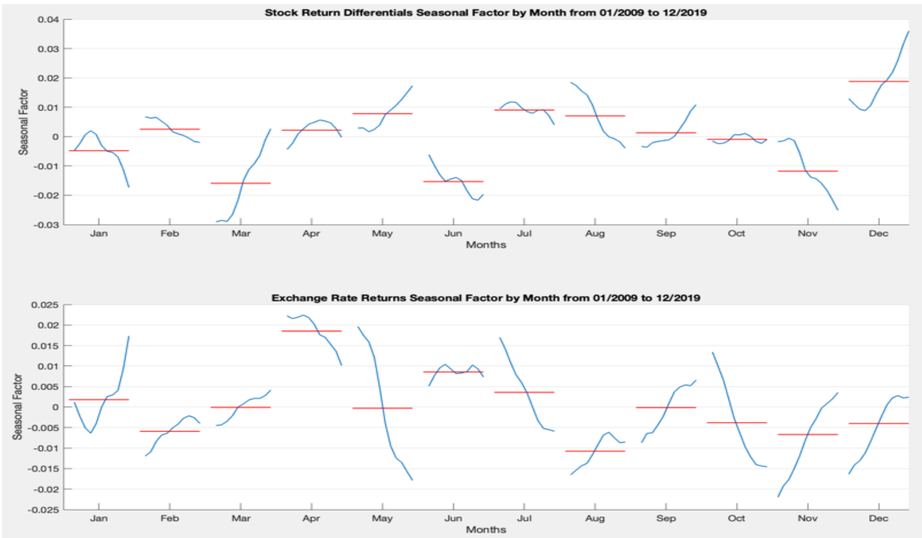


Figure A 10 - Seasonal Factors comparison from 01/2009 to 12/2019.

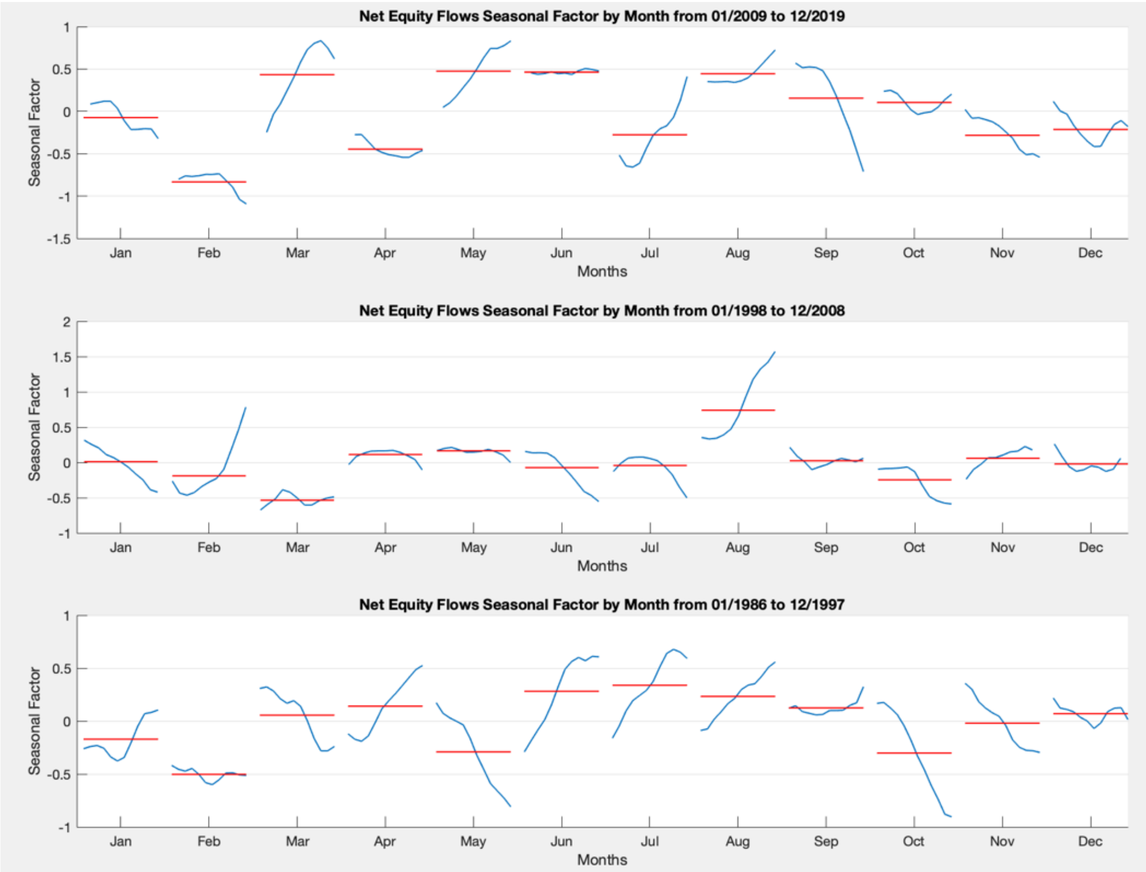


Figure A 11 - Seasonal Factors of Net Equity Flows by decades.

The blue line represents the behavior of each month's seasonal components, while the red line indicates the monthly average.
The analyzed time spans are: January 1986 until December 1997, January 1998 until December 2008, and January 2009 until December 2019.

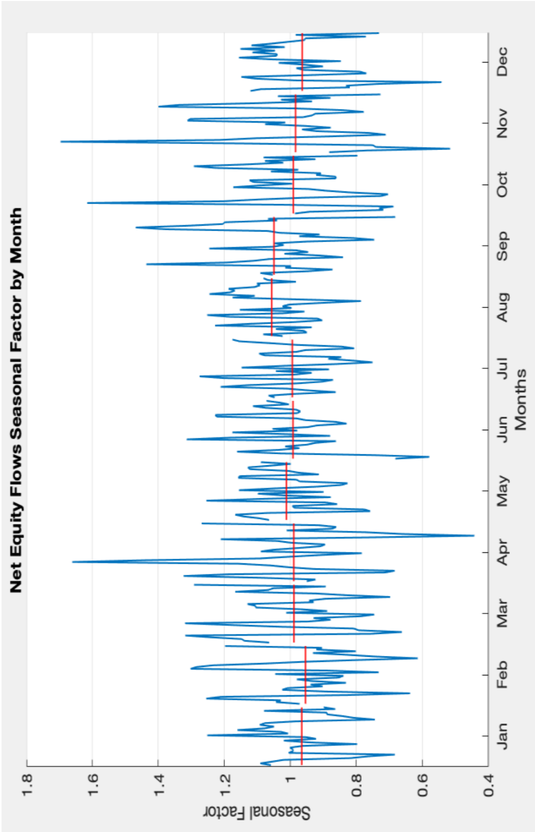


Figure A 12 - Seasonal Factor analysis of Net Equity Flows, using CAMPLET algorithm.

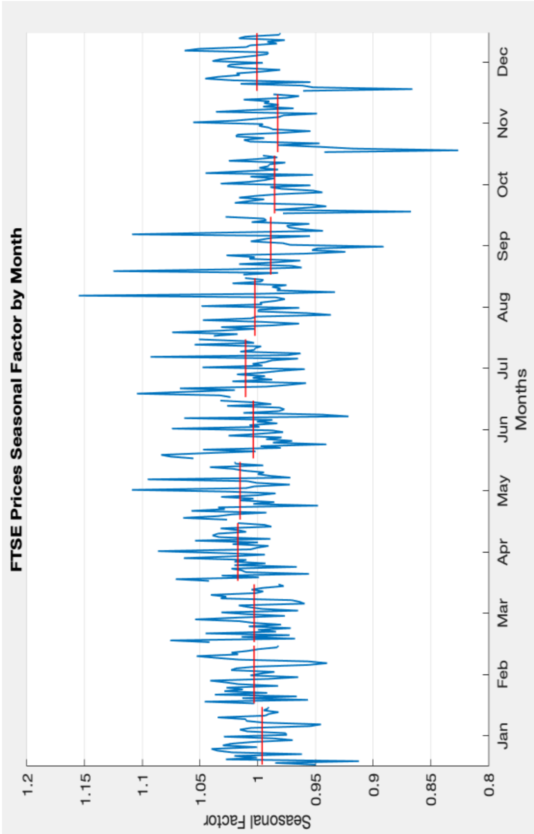


Figure A 13 - Seasonal Factor analysis of FTSE 100 Prices, using CAMPLET algorithm.

Figure A 14 - Seasonal Factor analysis of S&P 500 Prices, using CAMPLET algorithm.

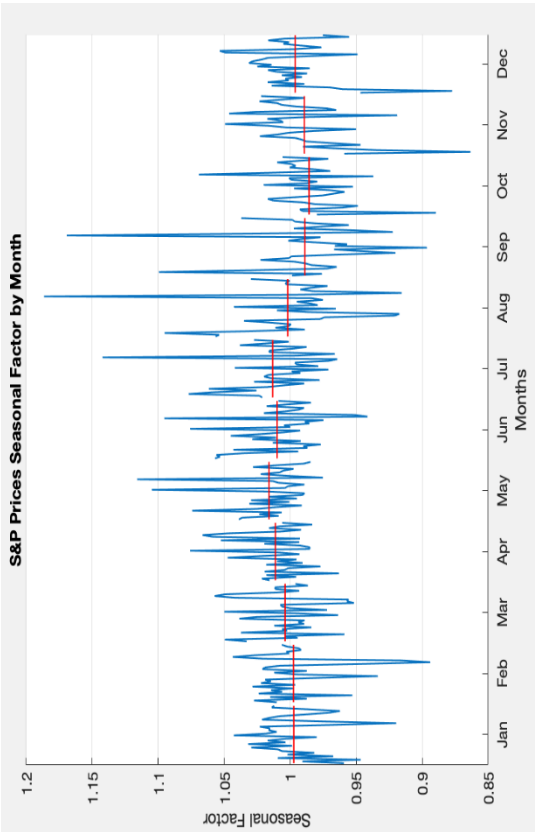
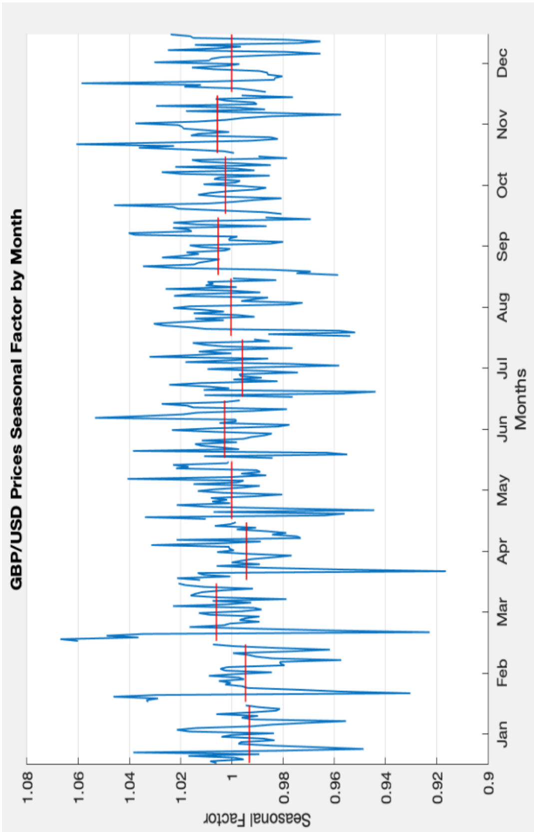


Figure A 15 - Seasonal Factor analysis of GBP/USD Prices, using CAMPLET algorithm.



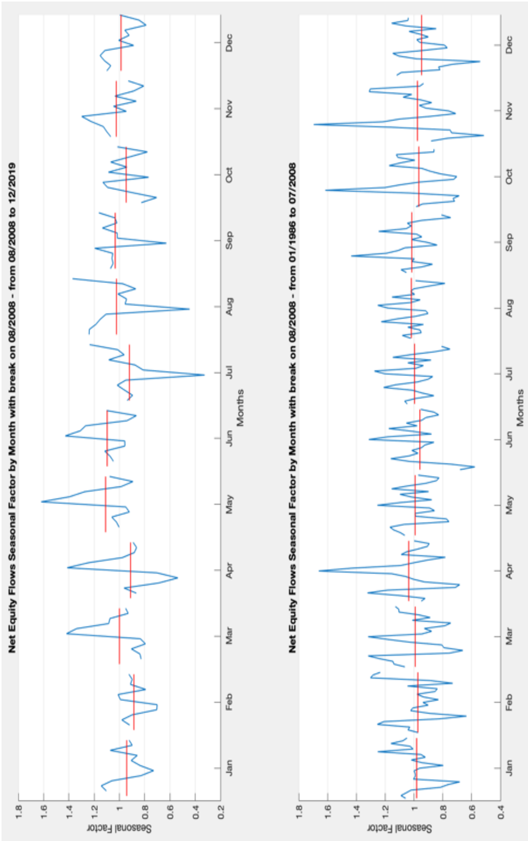


Figure A 16 - Seasonal Factor analysis of Net Equity Flows with break tests, using CAMPLET algorithm.

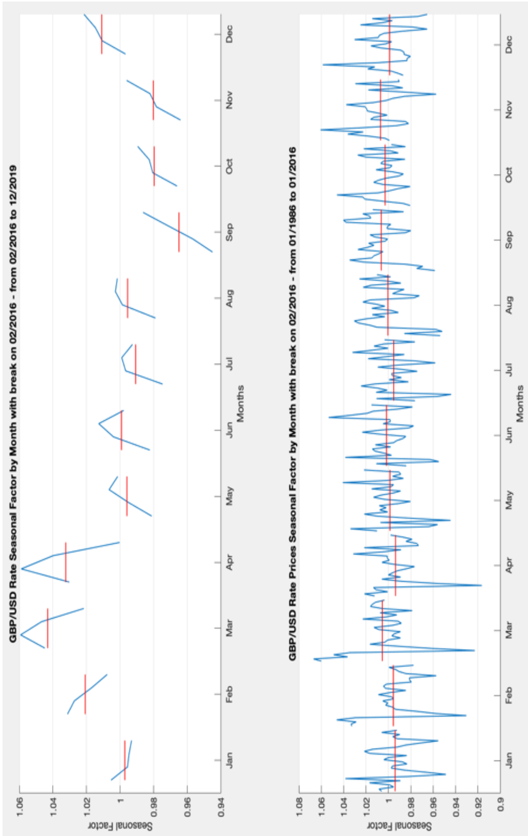


Figure A 17 - Seasonal Factor analysis of GBP/USD Prices with break tests, using CAMPLET algorithm.

Figure A 18 - Seasonal Factor analysis of S&P 500 Prices with break tests, using CAMPLET algorithm.

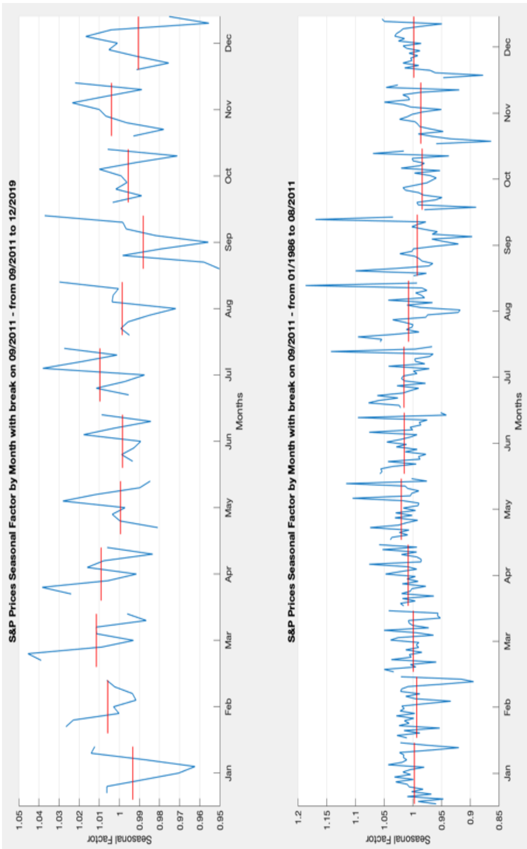
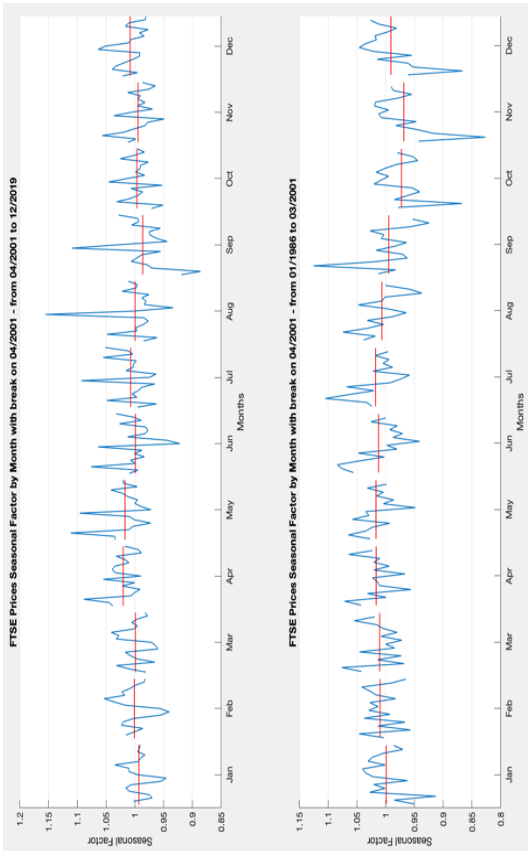


Figure A 19 - Seasonal Factor analysis of FTSE 100 Prices with break tests, using CAMPLET algorithm.



Date	Month	GBP/USD return	Bid-Ask spread	Return after spreads	Net profit per standard
2019	March	-0.0173	0.0004	-0.0169	-1694.4
2018	March	0.0185	0.0005	0.0180	1803.2
2017	March	0.0133	0.001	0.0123	1232.8
2016	March	0.0318	0.0007	0.0311	3113.6
2015	March	-0.0399	0.0004	-0.0395	-3951.7
2014	March	-0.0048	0.0003	-0.0045	-453.8
2013	March	0.0027	0.0003	0.0024	240.4
2012	March	0.0059	0.0006	0.0053	530.6
2011	March	-0.0140	0.0004	-0.0135	-1354.0
2010	March	-0.0043	0.0004	-0.0038	-384.0
2009	March	0.0012	0.0004	0.0008	76.6
2008	March	-0.0021	0.0004	-0.0016	-164.1
2007	March	0.0020	0.0004	0.0016	161.5
2006	March	-0.0090	0.0004	-0.0086	-858.6
2005	March	-0.0169	0.0004	-0.0165	-1648.4
2004	March	-0.0118	0.0004	-0.0114	-1140.9
2003	March	0.0060	0.0004	0.0056	561.5
2002	March	0.0070	0.0004	0.0066	657.0
2001	March	-0.0197	0.0004	-0.0193	-1930.7
2000	March	0.0084	0.0004	0.0080	800.2
1999	March	0.0048	0.0004	0.0044	438.1
1998	March	0.0174	0.0004	0.0170	1697.2
1997	March	0.0056	0.0004	0.0052	522.4
1996	March	-0.0033	0.0004	-0.0029	-290.8
1995	March	0.0246	0.0004	0.0242	2421.5
1994	March	-0.0009	0.0004	-0.0005	-45.3
1993	March	0.0634	0.0004	0.0630	6296.9
1992	March	-0.0117	0.0004	-0.0113	-1130.2
1991	March	-0.0862	0.0004	-0.0858	-8577.0
1990	March	-0.0185	0.0004	-0.0181	-1807.2
1989	March	-0.0327	0.0004	-0.0323	-3230.3
1988	March	0.0626	0.0004	0.0622	6221.5
1987	March	0.0389	0.0004	0.0385	3848.3
1986	March	0.0217	0.0004	0.0213	2127.4

Table A 2 - Net profits after transaction costs on the GBP/USD exchange rate.

The bid-ask spread quotes are available only from February 2012, and are taken from Datastream. The previous years were addressed by using a mean of the 2012-2019 sample (0.000422).
All Marches were analyzed, and the table represents the net profits of buying the American dollar. Negative returns correspond to the depreciation of the American dollar, and profits displayed as negative can be made by purchasing the British pound.

APPENDIX 2

From the Handbook on Seasonal Adjustment of 2018:

"The estimates of trend and seasonal components are obtained from cascade filtering that results from the convolution of various individual linear filters: (i) 12-term centered seasonal moving average; (ii) two 3 x (2n+1) seasonal moving averages; and (iii) the Henderson moving average. The 12-term centered seasonal moving average is defined as

$$D(B) = \left(\frac{1}{24}\right) B^{-6}(1 + B)(1 + B + B^2 + \cdots + B^{11})$$

where B is the backshift operator defined as $B^m y_t = y_{t-m}$ and $B^0 = 1$, and the seasonal moving averages as follows

$$S_t^{3x(2n+1)} = \frac{1}{3}\left(S_{t-12}^{(2n+1)} + S_t^{(2n+1)} + S_{t+12}^{(2n+1)}\right)$$

with $S_t^{(2n+1)} = \frac{1}{2n+1} \sum_{j=-n}^{n} SI_{t+12j}$

where $S_t^{3x(2n+1)}$ denotes the (3 x (2n + 1)) seasonal moving averages, and SI is the seasonal-irregular component (*de-trended value of the series*). The order of the moving average is selected from the irregular seasonal ratio (I/S) among the following moving averages: 3 x 3, 3 x 5 and 3 x 9.

The estimate of the trend-cycle is made by the application of one of three different Henderson linear filters available in the computer package, namely, the 9-, 13-, and 23-term. These filters developed by Henderson (1916) are based on summation formula which makes the sum of squares of the third differences of the smoothed series a minimum for any numbers of terms. In other words, the $\sum(\Delta^3 y_t)^2$ is minimized, where Δ is the difference operator and y_t is the output or smoothed series, if and only if $\sum(\Delta^2 h_k)^2$ is minimized, where h_k' are the weights, subject to the constraints that $\sum h_k = 1, \sum k h_k = 0$ and $\sum k^2 h_k = 0$ (Dagum (1978)).

The Henderson symmetric weight system of length *2n + 1*, where $m = n + 2$, is given by

$$h_k = \frac{315[(m-1)^2 - k^2][m^2 - k^2][(m+1)^2 - k^2][3m^2 - 16 - 11k^2]}{8m(m^2-1)(4m^2-1)(4m^2-9)(4m^2-25)}$$

(4.2)

To derive a set of 13 weights from (4.2), 8 is substituted for m and the values are obtained for each n from -6 to 6. The Henderson 13-term trend-cycle filter is thus given by,

$$\begin{aligned} H_{13}(B) = \; & -0.019B^{-6} - 0.028B^{-5} + 0.00B^{-4} + 0.065B^{-3} + 0.147B^{-2} + 0.214B^{-1} \\ & + 0.24B^{-0} + 0.214B^{1} + 0.147B^{2} + 0.065B^{3} + 0.00B^{4} - 0.028B^{5} \\ & - 0.019B^{6} \end{aligned}$$

(4.3)”.

BIBLIOGRAPHY

Abeln B., Jacobs J. P. A. M. (2015), *Seasonal adjustment with and without revisions: a comparison of X-13ARIMA-SEATS and CAMPLET*, CAMA Working Paper 25/2015, CAMA – Centre for Applied Macroeconomic Analysis.

Bhardwaj R. K., Brooks L. D. (1992), *The January anomaly: effects of low share price, transaction costs, and bid-ask bias*, Journal of Finance 47, 552-575.

Burnside C., Eichenbaum M., Kleshehelski I., Rebelo S. (2006), *The returns to currency speculation*, NBER Working Papers, no 12489, August.

Burnside C., Eichenbaum M., Rebelo S. (2007), *The returns to currency speculation in emerging markets*, AEA Papers and Proceedings 97(2), 333–338.

Buys-Ballot C. (1847), *Les changements périodiques de température*, Utrecht: Kemink et Fils.

Cenedese G., Payne R., Sarno L., Valente G. (2015), *What do stock markets tell us about exchange rates?*, Review of Finance 20, 1045-1080.

Chen Q. (2013), *Risk and seasonal effects: international evidence*, Journal of Chinese Economic and Business Studies 11(4), 299-311.

City of London (2022), *London leads global financial rankings for the second year running*, London, 27 January 2022.

Clarida R., Davis J., Pedersen N. (2009), *Currency carry trade regimes: Beyond the Fama regression*, Journal of International Money and Finance, Elsevier.

Coppola A., Maggiori M., Neiman B., Schreger J. (2021), *Redrawing the map of global capital flows: the role of cross-border financing and tax havens*, The Quarterly Journal of Economics 136, 1499-1556.

Cumby R. E., Obstfeld M. (1981), *A note on exchange-rate expectations and nominal interest differentials: a test of the Fisher hypothesis*, Journal of Finance 36, 697–704.

Dickey D., Fuller W. (1979), *Distribution of the estimator for autoregressive time series with a unit root*, Journal of the American Statistical Association 74, 427-431.

Draper P., Paudyal K. (1997), *Microstructure and seasonality in the UK equity market*, Journal of Business Finance and Accounting 24, 1177-1204.

Eurostat (2018), *Handbook on Seasonal Adjustment 2018 edition*, Publications Office of the European Union, Luxembourg.

Fama E. (1984), *Forward and spot exchange rates*, Journal of Monetary Economics 14, 319–338.

Fisher R. A. (1920), *A mathematical examination of the methods of determining the accuracy of observation by the mean error, and by the mean square error*, Monthly Notices of the Royal Astronomical Society 80, 758-770.

Floros C., Salvador E. (2014), *Calendar anomalies in cash and stock index futures: International evidence*, Economic Modelling 37, Elsevier.

Galati G., Heath A., McGuire P. (2007), *Evidence of carry trade activity*, BIS Quarterly Review, September 2007, 27-41.

Gauss C. F. (1809), *Theoria Motus Corporum Coelestium in Sectionibus Conicis Solem Ambientium*, F. Perthes and I. H. Besser, Hamburg.

Girardin E., Salimi Namin F. (2019), *The January effect in the foreign exchange market: Evidence for seasonal equity carry trades*, Economic Modelling 81, 422-439, Elsevier.

Gómez V., Maravall A. (1997), *Programs TRAMO and SEATS: Instructions for the user (beta version: June 1997)*, Working Paper No 97001, Dirección General de Anélisis y Programación Presupuestaria, Ministerio de Economía y Hacienda, Madrid.

Gultekin M. N., Gultekin N. B. (1983), *Stock market seasonality: international evidence*, Journal of Financial Economics 12, 469-481, Elsevier.

Hansen L. P., Hodrick R. J. (1980), *Forward exchange rates as optimal predictors of future spot rates: an econometric analysis*, Journal of Political Economy 88, 829–853.

Haugen R. A., Lakonishok J. (1988), *The incredible January effect: the stock market's unresolved mystery*, Homewood, IL: Dow Jones-Irwin.

Heyde C. C., Seneta E., Crépel P., Fienberg S. E., Gani J. (2001), *Statisticians of the Centuries*, Springer New York, New York.

Jarque C., Bera A. (1987), *A test for normality of observations and regression residuals*, International Statistical Review 55, 163-172.

Keim D. B. (1989), *Trading patterns, bid-ask spreads, and estimated security returns: the case of common stocks at calendar turning points*, Journal of Financial Economics 25, 75-97.

King W. (1924), *An Improved Method for Measuring the Seasonal Factor*, Journal of the American Statistical Association 19 (147), 301-313.

Kohers T., Kohli R. K. (1992), *The yearend effect in stock returns over business cycles: a technical note*, Journal of Economics and Finance 16, 61-68.

Kramer C. (1994), *Macroeconomic seasonality and the January effect*, Journal of Finance 49, 1883-1891.

Kruskal W. H., Wallis W. A. (1952), *Use of ranks in one-criterion variance analysis*, Journal of the American Statistical Association 47, 583-621.

Kwiatkowski D., Phillips P. C. B., Schmidt P., Shin Y. (1992), *Testing the null hypothesis of stationarity against the alternative of a unit root*, Journal of Economics 54, 159-178.

Lakonishok J., Shleifer A., Thaler R., Vishny R. (1991), *Window dressing by pension fund managers*, American Economic Review 81/2, 227-231.

Laplace P. S. (1812), *Théorie analytique des probabilités*, Mme Ve Courcier, Imprimeur-Libraire pour les Mathématiques, Paris.

Legendre A. M. (1805,. *Nouvelles Méthodes pour la Détermination des Orbites des Comètes*, Firmin Didot, Paris.

Lengwiler Y. (2022), *X-13 Toolbox for Seasonal Filtering*, MATLAB Central File Exchange.

Levene H. (1960), *Robust tests for equality of variances*, Contributions to Probability and Statistics: Essays in Honor of Harold Hotelling, Stanford University Press, Stanford, 278-292.

Li B., Liu B., Fin R. B. F, Su J. J. (2011), *Monthly seasonality in currency returns: 1972-2010*, JASSA – The Finsia Journal of Applied Finance, March 2011.

Logan A. (2001), *The United Kingdom’s small banks’ crisis of the early 1990s: what were the leading indicators of failure?*, Publications Group, Bank of England, London.

Macaulay F.R. (1931), *The Smoothing of Time Series*, National Bureau of Economic Research, New York.

McQuade P., Schmitz M. (2019), *America first? A US-centric view of global capital flows*, Working Paper Series 2238, European Central Bank, Frankfurt am Main.

Meese R., Rogoff K., (1983), *Empirical exchange rate models of the seventies. Do they fit out of sample?*, Journal of International Economics 14, 3–24.

Menyah K., Paudyal K. (1996), *The determinants and dynamics of bid-ask spreads on the London Stock Exchange*, Journal of Financial Research 19, 377-394.

Miller M. (2022), *BUZZ-COMMENT-GBP/USD usually gains in April, but maybe not this year*, Reuters, April 1st 2022.

Ng S., Perron P. (2001), *Lag length selection and the construction of unit root tests with good size and power*, Econometrica 69, 1519-1554.

Nordstokke D. W., Zumbo B. D. (2010), *A new nonparametric Levene test for equal variances*, Psicologica 31, 401-430.

Ogden J. P. (1990), *Turn-of month evaluations of liquid profits and stock returns: a common explanation for the monthly and January effects*, Journal of Finance 45, 1259-1272.

Persons W.M. (1919), *Indices of general business conditions*, Review of Economic Statistics 1, 111-205.

Phillips P. C. B., Perron P. (1988), *Testing for a unit root in time series regression*, Biometrika 75, 335-346.

Platun A., Sibande X., Gupta R., Wohar M. E. (2019), *Rise and fall of calendar anomalies over a century*, North American Journal of Economics and Finance 49, 181-205.

Roll R. (1983), *Vas ist das? The turn of the year effect and the return premia of small firms*, Journal of Portfolio Management, Winter, 18-28.

Shiskin J. (1957), *Electronic computers and business indicators*, Occasional Paper No 57, National Bureau of Economic Research, New York.

Shiskin J., Young A. and Musgrave J.C. (1967), *The X11 variant of the Census method II seasonal adjustment program*, Technical Paper No 15, US Bureau of the Census, Washington DC.

Shiskin J. (1978), *Seasonal adjustment of sensitive indicators*, Seasonal Analysis of Economic Time Series, Zellner A. (ed.), US Bureau of the Census, Washington DC.

Stoll H. R., Whaley R. E. (1983), *Transaction costs and the small firm effect*, Journal of Financial Economics 12, 57-80.

SITOGRAPHY

CFA Institute

Federal Reserve Economic Data | FRED | St. Louis Fed

HL - Hargreaves Lansdown

Investing.com – GBP/USD

Investing.com – S&P 500

Investopedia

NASDAQ

Refinitiv Datastream

Stata

The Wall Street Journal Markets

Treasury International Capital (TIC) System | U.S. Department of the Treasury

United States Census Bureau – About X-13

United States Census Bureau – Q&A

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