ERASMUS UNIVERSITY ROTTERDAM

Erasmus School of Economics

Thesis Proposal [Bachelor of Econometrics and Operations Research]

Title of Thesis: Seasonality Presence in Global Stock Index Returns

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Abstract

Seasonality in stock index returns comes in many forms, some of which includes the Halloween effect and the seasonal affective disorder (SAD) effect. On top of these two effects, various other factors analyzed by previous literatures also comes into play, mainly those from the papers by Jacobsen & Zhang (2013) and Kamstra et al. (2008). This paper analyzes seasonality in stock index returns based on these two literatures, and includes further extensions on this topic by including a new seasonal variable of specific options expiration days as well as the use of panel regression on 15 different indices. Our findings shows significance in these seasonal variables, although it widely varies between indices. Based on these results, a simple trading strategy is then constructed in order to utilize these effects to our advantage.

Contents

1 Introduction

Stock index returns has always been fluctuating throughout the years, yet its predictability remains unanswered. Many believe that these fluctuations can somewhat be anticipated to a certain degree beforehand, and that it shows a discernible pattern throughout a time period, as opposed to a random walk (Lo & MacKinlay, 1987). Based on the multiple studies done on this topic, the seasonal effects in stock returns are mostly noticeable on a monthly or annual basis. This paper will analyze this seasonal property even further by examining various stock index monthly and daily returns, checking the significance of its seasonal properties.

Having a full knowledge about the seasonal effects of the stock returns may give a substantial advantage to an individual when constructing a portfolio. Periods with positive seasonal effects can be emphasized more than those with unfavorable seasonal effects, resulting in an improved portfolio. The findings in this paper will help contribute to our current knowledge about the seasonality in stock returns, which will hopefully enable a more efficient portfolio construction taking into account these seasonal effects in the future. The ability to create such efficient portfolios may encourage banks from leaning towards riskier investments, which will have an impact on the financial and economic stability (Laeven & Levine, 2008).

As mentioned by Jacobsen & Zhang (2013), seasonality in stock returns may not be consistent throughout a long period of time. For example, the effect of Christmas on stock returns has only started appearing in 1830, and it will not be a surprise if a currently existing seasonal effect may disappear in the future. Given the ever-changing nature of the long-term seasonality, this paper focuses on the seasonal effects in the past 50 years, which should give a reasonable estimate and forecasting power for the next few years. However, a thoroughly accurate recognition of these reoccurring seasonal effects may prove to be challenging. There may also be possibility of error in sampling and data mining around certain time periods that can be mistaken for seasonal effects (Lakonishok, 1987). It is thus interesting to see whether the seasonal effects are real, and if they do, up to what extent do they affect the stock index returns.

The first part of this paper consists of a replication of the studies from Jacobsen & Zhang (2013) and Kamstra et al. (2003), while the second part examines further extensions on these methods. Our purpose is to analyze the seasonal effects defined by the existing literatures, where various effects such as monthly effects, Halloween effect, Monday effect and many more are examined. One of these seasonal effects will include the Seasonal Affective Disorder (SAD), where it is believed that longer hours of night in a country leads to a higher daily stocks return. Our results indicates that most of these seasonal properties do show a significant effect in most countries, although it highly varies from index to index. Further extensions are then applied on the models, which includes the incorporation of both models from Jacobsen & Zhang (2013) and Kamstra et al. (2003) in a single model, an additional seasonal dummy representing the options expiration periods, as well as a panel regression approach on these methods.

A trading strategy can be formulated given the seasonal effects of each index, for example the pro-SAD strategy constructed by Kamstra et al. (2003) where it is suggested to invest in an index located in the Northern Hemisphere, such as the Canadian index, during its fall and winter periods then reallocate all 100% of the investment to Australia during its own fall and winter periods. However, such a strategy may not necessarily bear fruit given our findings since the SAD effect is mostly present only on Western countries in the Northern Hemisphere, thus excluding Australia. It may still be a good idea, however, to increase or intensify investment activities in the SAD-affected countries during the fall and winter periods. Given the varying results of each index, there is no single best trading strategy that can be used for all indices without any adjustments. For example, it is profitable to increase investments before the end of the tax year in Australia, but on the other hand the Japanese index performs significantly worse during the end of the tax year.

2 Literature Review

Many studies, such as those from Jacobsen & Zhang (2013) and Kamstra et al. (2003), have tried to find a discernible seasonal pattern within the stock index returns. The resulting metrics of these papers show significant effects of certain time periods on different stock index performances across the globe. The findings by Rozeff & Kinney (1976) also suggested the discernible presence in monthly seasonality, where the returns of the stocks in the New York Stock Exchange (NYSE) is consistently higher in January compared to other months. The monthly seasonality also widely differs between stock markets, as shown that Australian stocks display stronger seasonal effects compared to the NYSE stocks, which peaks in July instead of January. It is also concluded that the efficient market hypothesis does not hold in the case that stock returns vary depending on the month, although it is still not possible for investors to make clear profit based on these monthly variations alone. The paper by Steeley (2001) examined a higher frequency intra-week seasonal property by analyzing the day of week seasonality as well as the weekend effect. The findings suggested that there are other drivers behind the seasonality besides day of the week alone, such as an information announcement effect where new announcements are usually heavily clustered around Tuesdays to Thursdays and less around Mondays or Fridays.

Given the significance of these findings, there should theoretically be an optimal portfolio such that the return distribution is higher than that of a randomly created portfolio (Chunhachinda et al., 1997). A sample trading strategy of buying past good performing stocks and selling the underperfoming ones does show a significant abnormal returns in the long run, according to the paper by Jegadeesh & Titman (1991). Although this trading strategy involves holding the past winners and losers for the following 6 months, the same concept can be applied with a shorter time frame in order to utilize the seasonal effects during the year. The ability to construct such a portfolio will be highly appreciated, which further motivates the purpose of this paper.

As one of the literatures replicated in this paper, Jacobsen & Zhang (2013) analyzes the 317-year UK stock index monthly returns from 1693 to 2010. The paper takes a deeper look at the seasonal effects of each month in the span of 317 years, as well as the “Halloween effect”. The Halloween effect, or “Sell-in-May”, is a seasonal effect where stocks tend to perform worse during the summer compared to during the winter. The month of May is believed to be the start of the bear market, where stocks perform poorly, which gives the phrase “Sell in May, and go away”. The phrase continues in “But remember to come back in September”, as September signals the start of the bull market where stocks are expected to perform better than other periods throughout the year (Bouman & Jacobsen, 2002).

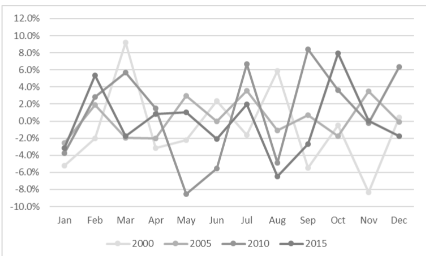
The second paper from Kamstra et al. (2003) analyzes the effect of SAD on the stock index returns. SAD is a disorder that affects places with few hours of daylight, most evidently during the fall and winter periods where nights are longer compared to the rest of the year. As the paper cited, fewer hours of daylight show a significant correlation with an increased level of depression, which then corresponds to fewer risk-taking behaviors and thus a change in stocks performance. As the risk aversion increases, the risky investments in that location will yield relatively higher returns due to the lower demand of risky assets which lowers the initial prices (Kamstra et al., 2003). The SAD is expected to have a bigger impact on countries with extreme latitudes such as Canada and Australia compared to countries around the equator, due to the variance in number of daylight within a day in those countries.

3 Data

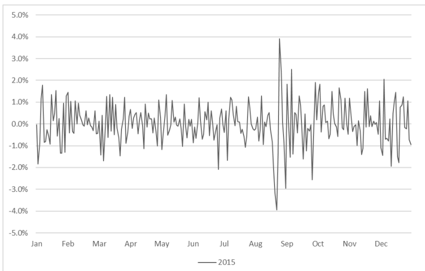
As mentioned above, replicating the full 317-year data sample from the paper by Jacobsen & Zhang (2013) is not feasible given the time and resources. The paper by Kamstra et al. (2003) also uses a data set of up to 70 years, which is unfortunately also unachievable given our circumstances. Given the available resource, the data on stock returns used is then obtained solely from Bloomberg to retain data selection consistency. The data contains the daily stock index returns spanning over a fifty-year period from 1966 to 2016, which we believe is a good representation for the current stock market. The data used consists of the closing daily trade prices of 15 different stock market indices across 12 different countries. The indices used are selected based on its relevance in the current global economy as well as its country's latitude. With the significant role of American and European stocks in the global economy, heavier emphasis on these indices are placed in our sample selection. The 12 countries chosen covers the latitudes necessary to reduce the bias in our SAD estimation when replicating the paper by Kamstra et al. (2003). In replicating the returns on SAD regression, data of only up to 31 December 2000 is used in order to obtain an estimation closer to that of the original paper.

In analyzing the various stock markets' performance, the following indices are chosen as representative for each respective stock market listed in *Table 1*, along with its monthly options expiration day. Each country is represented by one index each, other than the United States where three indices consisting of S&P500 index, Dow Jones index and NASDAQ index are included. Each index used are denoted by its country or financial center, other than the three US-based indices. The options expiry date is further elaborated in the extensions methodology section. The monthly seasonality and Halloween effect regression is done by only using the monthly compounded returns of S&P500 from 1966 to 2016. *Figure 1* shows the monthly and daily returns of the S&P500 index in the recent years.

Figure 1: S&P500 index returns



(a) Monthly returns



(b) Daily returns

[1] Figure 1 shows the monthly and daily returns of the S&P500 index. Figure (a) shows the monthly compounded returns for 2000, 2005, 2010 and 2015. Figure (b) shows daily returns of the index in 2015.

Table 1: Indices used for each country

	Index	Start Period	Expiry Day	Latitudes
Netherlands	AEX	Jan 1983	3rd Fri	52°N
Australia	ASX 200	May 1992	3rd Thu	35°S
France	CAC 40	Jul 1987	3rd Fri	48°N
German	DAX	Jan 1971	3rd Fri	39°N
Dow Jones	DJI	Jan 1966	3rd Fri	41°N
EUR	Euro Stoxx 50	Dec 1988	3rd Fri	50°N
London	FTSE 100	Dec 1983	3rd Fri	51°N
Hong Kong	Hang Seng	Apr 1974	Last Day	41°N
Indonesia	JCI	Nov 1991	-	6°S
Russia	MICEX	Sep 1997	3rd Fri	55°N
NASDAQ	IXIC	Feb 1971	3rd Fri	41°N
Japan	Nikkei 225	Jan 1970	2nd Thu	35°N
S&P500	S%P500	Dec 1965	3rd Fri	41°N
Canada	S&P/TSX	Feb 1971	3rd Fri	43°N
South Africa	ZADOW	Oct 1998	-	34°S

[1] Table 1 shows the stock index used for each country, with the execption of US-based indices S&P 500, Dow Jones, and NASDAQ. The start period obtained from Bloomberg is listed for each index, along with the monthly options expiration day and each country's latitude.

The data on hours of night per day is obtained by replicating the measurement methods used by Kamstra et al. (2003), in which the required input is only the latitude of the corresponding location. These latitudes are be obtained from the database of Infoplease, based on each index's financial district. As we require a multi-year time series data on each country's environmental properties to replicate the SAD measurement model, we assume that monthly averages in temperature, precipitation and cloud cover hold the same patterns over any given year. We obtain the monthly temperature and precipitation averages from the World Bank database, measured from the period 1961-1999. Although this data may be relatively outdated, we believe that it still gives a good representation of the current environmental situations despite the present issues with global warming and climate change. The data on cloud cover is obtained from Weather Spark, which uses the 2016 monthly cloud cover for each country. The data used for cloud cover, precipitation and temperature shows the different levels of environmental factors in each month of the year, but it does not vary over the years. In examining the European stock index, the average climate data of the Netherlands, Germany, France and United Kingdom is used.

In the full data sample, we detected some inconsistency in the number of trading days within the fifty years among the different indices. This inconsistency can be mostly explained by the different public holidays in these different countries, which stacks up into a noticeable difference in a fifty-year period. Some indices do not even date back far enough for us to retrieve a fifty-year period data, with the shortest index only reaching back to 1998. The dataset used for the replication methods does not require the same number of observations, as each index is examined separately. However, the panel regression extension does require the same number of observations for each index, which will be further elaborated in the extensions section. For this purpose, the panel data set is filtered by only using trading days in which all 15 different indices perform trading from 1998 to 2016. We do realize that this may lead to a slight sample selection bias, but considering the relatively small number of country-specific public holidays per year, the few omitted observations should not have any substantial influence on the full model. A very small number of trading days have missing information on the closing index price, and these observations are omitted as well. These omitted missing observations adds up to less than 0.1% of the total number of observations, which we consider to still be in an acceptable range.

The descriptive statistics of the daily returns from every index used in this paper is reported in *Table 2*, along with the various starting dates obtainable from Bloomberg. The table reports both the statistics of the full data sample up till December 2016, as well as the restricted sample that contains only data up to December 2000.

Table 2: Descriptive statistics of each indices

	Mean	**s.d.**	**Min**	**Max**	**Skewness**
Netherlands	0.040	1.430	-10.922	13.338	0.010
Australia	0.028	1.357	-14.537	9.965	-0.468
France	0.027	1.507	-11.047	13.141	0.049
German	0.044	1.405	-11.640	13.397	-0.040
Dow Jones	0.029	1.034	-22.611	12.376	-0.594
EUR	0.028	1.458	-10.122	12.939	0.044
London	0.030	1.274	-13.548	13.868	-0.167
Hong Kong	0.051	1.750	-33.416	18.905	-0.718
Indonesia	0.046	2.276	-27.009	38.709	0.949
Russia	0.059	2.922	-24.247	33.165	0.335
NASDAQ	0.042	1.234	-11.350	14.173	-0.079
Japan	0.029	1.696	-99.719	13.195	-17.566
S&P500	0.030	1.037	-20.467	11.580	-0.616
Canada	0.031	1.192	-11.521	15.766	-0.293
South Africa	0.048	1.732	-12.132	13.344	-0.177

	Mean*	**s.d.***	**Min***	**Max***	**Skewness***
Netherlands	0.068	1.251	-10.829	11.827	-0.127
Australia	0.021	1.079	-6.237	6.940	0.050
France	0.046	1.328	-11.047	9.513	-0.211
German	0.051	1.244	-11.640	9.103	-0.159
Dow Jones	0.032	0.973	-22.611	12.376	-1.128
EUR	0.055	1.134	-9.855	8.126	-0.149
London	0.049	1.126	-13.548	7.697	-0.550
Hong Kong	0.070	1.887	-33.416	18.905	-0.990
Indonesia	0.002	2.994	-27.009	38.709	1.306
Russia	-0.033	4.794	-24.247	33.165	0.305
NASDAQ	0.048	1.061	-11.350	10.477	-0.510
Japan	0.034	1.766	-99.719	13.195	-23.466
S&P500	0.035	0.933	-20.467	9.099	-1.213
Canada	0.035	1.050	-11.126	15.766	-0.205
South Africa	0.070	1.596	-9.093	7.088	-0.243

[1] Table 2 shows the descriptive statistics of each listed index. The first part of the table shows the statistics of the full sample of each index up to December 2016, while the second part denoted with stars (*) shows the statistics of the sample up to December 2000.

As expected from the daily returns data, the mean of each index is very close to zero, with the largest mean being 0.06%. No index shows any negative mean other than the Russian index during the 1997 to 2000 period, which may be mainly due to the 1998 Russian financial crisis and the relatively shorter data period of only 3 years.

4 Methodology

4.1 Replications

In replicating the results from both papers, a simple linear regression is used on the monthly and daily returns of each stock index. Dummy variables are added for each seasonal effect, with value 1 for every affected monthly or daily return and 0 otherwise.

Monthly and Halloween Effect Seasonality

The regression for Halloween and monthly seasonal effects from Jacobsen & Zhang (2013) are done by only regressing the compounded monthly returns of each index on a constant and each dummy variables. The regressions are done separately for each seasonal effect, up to a total of 13 regressions for a single stock index. The first set of regressions for monthly seasonality is done by doing 12 regressions, each with a constant and a dummy variable for each particular month. The next regression for the Halloween effect includes a constant and a dummy variable for days that are between November and April, as done by Bouman & Jacobsen (2002).

The regressions for examining monthly seasonality are done as:

$$r_t = \alpha + \beta_m D_{mt} + \varepsilon_t \tag{1}$$

with r_t denoting the compounded monthly returns for month t of the stock index of interest and α denoting the average returns throughout the year. D_{mt} indicates a dummy for each calendar month from January to December (m = 1, 2, . . . , 12), with value 1 if t is month m and 0 otherwise. β_m shows us how much do the returns of each month m deviate from the returns during the rest of the year.

The regression for examining the Halloween effect is done in accordance to the methods by Bouman & Jacobsen (2002):

$$r_t = \alpha + \beta_{Halloween} S_t + \varepsilon_t \tag{2}$$

with S_t denoting a dummy with value 1 if month t is in the period between November and April, and value 0 otherwise. Examining the Halloween dummy coefficient $\beta_{Halloween}$ allows us to inspect the significance of the "Sell-in-May" property. If stock returns during the winter are indeed substantially higher than that from the rest of the year, $\beta_{Halloween}$ will be significantly positive.

SAD Effect

In replicating the paper by Kamstra et al. (2003), an autoregressive model up to two lags is used with daily stock returns as the dependent variable. Dummy variables are also be included in the model, with dummies for periods following a weekend and for periods at the beginning and end of a tax year. A seasonal dummy for the fall season is also be used for each country, along with parameters for each country's environmental situations such as cloud cover, precipitation, and temperature. Finally, the number of daylight in a day at period t is be included in order to measure the SAD effect. The number of daylight within a day is measured by the total hours of night in a day, which is calculated based on the day, month and latitude of the country.

The hours of night in a day can be calculated a metric for the sun's inclination angle, λ_t, which is measured by:

$$\lambda_t = 0.412 \cdot \sin\left[(\frac{2\pi}{365})(julian_t - 80.25)\right] \tag{3}$$

where $julian_t$ indicates in which part of the year is day t, with value 1 for January 1, 2 for January 2, up to 365 or 366 for leap years. Once λ_t is obtained, it can be used along with the country's latitude δ to estimate the hours of night in a day H_t by using the formula:

$$H_t = \begin{cases} 24 - 7.72 \cdot \arccos\left[-\tan(\frac{2\pi\delta}{360})\tan(\lambda_t)\right] & \text{in the Northern Hemisphere} \\ 7.72 \cdot \arccos\left[-\tan(\frac{2\pi\delta}{360})\tan(\lambda_t)\right] & \text{in the Southern Hemisphere} \end{cases}$$

with arccos being the arc cosine of the function. Given H_t, the SAD effect of time t is measured by the function:

$$SAD_t = \begin{cases} H_t - 12 & \text{for trading days in fall and winter} \\ 0 & \text{otherwise} \end{cases}$$

where SAD_t is an indicator on the hours of night in a day, relative to the average hours of nights in a day on a given location and period (assumed to be 12).

The regression is done as an autoregressive model with two lags, with the daily stock index returns as the dependent variable. The model is described as:

$$\begin{aligned} r_t = \alpha &+ \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} \\ &+ \beta_{Fall} D_t^{Fall} + \beta_{SAD} SAD_t + \beta_{Cloud} Cloud_t \\ &+ \beta_{Precipitation} Precipitation_t + \beta_{Temperature} Temperature_t + \varepsilon_t \end{aligned} \tag{4}$$

with r_{t-1} and r_{t-2} denoting the first and second lag of the daily returns respectively. D^{Monday} gives the value 1 for days following a weekend, which usually land on Mondays, and 0 otherwise. D_t^{Tax} has the value 1 for the first 5 days and the last day of the tax year, with 0 otherwise. Different tax years of different countries are taken into account in creating the dummy variable. The tax year begins on January 1 for most countries such as United States, Canada, Germany and Japan. Some countries start their tax year on a different date, such as April 6 in the United Kingdom, July 1 in Australia, and March 1 in South Africa. D_t^{Fall} has the value 1 for days in the fall season, and 0 otherwise. The dummy D_t^{Fall} is different for some countries from different latitudes, as fall lands from September to November in the Northern Hemisphere but it lands from March to May in the Southern Hemisphere. $Cloud_t$, $Precipitation_t$ and $Temperature_t$ reports the cloud cover percentage, precipitation and temperature (°Celcius) of the country for a given day t. The environmental factors are recorded in a monthly basis that is repeated every year for each country, assuming that there is no substantial change in the monthly levels and the cycle of these factors over the years. The resulting coefficients of the regression depict the magnitudes and the significance of each parameter.

After further examination of the correlation between each variables, a slight alteration from the original model has been applied, where the climate conditions such as temperature, precipitation and cloud cover in a country are not included in the model due to the high correlativity between these metrics and the SAD measurement. We believe that the high correlation is mainly caused by the recurring and monthly nature of our climate conditions data, as opposed to the continuous daily time series used by Kamstra et al. (2003). The findings from Kamstra et al. (2003) also suggest that the climate conditions have no significant effect on the model, which condones our alteration of the model. The final model used for the regression is then defined as:

$$\begin{aligned} r_t = \alpha + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} \\ + \beta_{Fall} D_t^{Fall} + \beta_{SAD} SAD_t + \varepsilon_t \end{aligned} \tag{5}$$

where temperature, precipitation and cloud cover parameters are removed from the previous model.

4.2 Extensions

Aside from replicating the results of Jacobsen & Zhang (2013) and Kamstra et al. (2003), some further extensions of these papers are performed in this paper. The extensions performed in this paper include:

Halloween dummies and options expiration day dummies inclusion

The first extension is done by including variables from both replicated papers, which may provide a new insight on each seasonal effect. There also exists a possibility that some of the previously significant included variables may end up being statistically insignificant due to endogeneity between these variables. The variable extracted from the first paper is only the Halloween dummy, as the individual dummies for each month of the year will introduce a case of multicollinearity when combined with the other dummy variables. The climate condition parameters of temperature, precipitation and cloud cover are not included as well, due to the high correlation with the SAD variable.

As mentioned by the Chicago Board Options Exchange (CBOE), the American options expiring date is mostly set on the third Friday of the expiring month, and moved to the preceding Thursday in cases where the third Friday is a holiday. This effect is taken into account by including a dummy for third Fridays of every month. Non-American options may not necessarily follow this rule, and each country's options expiration day is used for its corresponding stock index. Indices that do not follow the American options expiration date are the Japanese, Australian and Hong Kong indices, which expires on the second Thursday, third Thursday and last trading day of the month respectively. The Indonesian and South African indices do not provide any options contract, and thus the dummy assigned to these indices will be empty.

The new model constructed with the first two extensions is then defined as:

$$\begin{aligned} r_t = \alpha + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} \\ + \beta_{Fall} D_t^{Fall} + \beta_{SAD} SAD_t + \beta_{Halloween} D_t^{Halloween} + \beta_{Expiry} D_t^{Expiry} + \varepsilon_t \end{aligned} \tag{6}$$

where $D_t^{Halloween}$ has the value 1 for days between November and April, and value 0 otherwise. The dummy for options expiration days D_t^{Expiry} has a value of 1 for third Fridays of each month and 0 otherwise for all countries except the Japanese, Australian, Hong Kong, Indonesian and South African indices, where each index has its own corresponding options expiration dummy as defined beforehand.

The forecasting power of the models are compared by comparing their mean squared prediction error (MSPE) with a rolling-window regression. The four models being compared are the original SAD model without any extra dummies, the model with additional Halloween dummy, the model with additional options expiration dummy, and the full model with both extra dummies. The rolling window forecast is used due to the instability and the ever-changing nature of the daily stock returns. The rolling window size used in the regression is set to 500 trading days, which is equivalent to around a window size of 2 calendar years. The resulting coefficients of the regression in a single window is then used to forecast the next day's stock return of the index, which is compared with the actual return of that day to obtain the prediction error. The regression of the full window size produces a vector of prediction errors, from which the MSPE of the model can be acquired by taking the mean of the squared prediction errors. The model with the lowest MSPE signifies the best forecasting power, although a minor difference in MSPE may not indicate any definite conclusion.

Panel Regression

A panel regression is applied into the model as an extension, which may give us more insight on the seasonal parameters. The nature of our data sampling in all the indices supports the use of a fixed effect model instead of a random effect model. According to Hsiao (2007), panel data analysis has advantages over individual cross section or time series data, which includes a more accurate inference of parameters along with simpler computations and statistical inference due to the higher degrees of freedom. The use of panel regression allows us to examine the effects of each seasonal property in all the indices as a whole, taking into account the differences of countries in the Northern Hemisphere and the Southern Hemisphere. The panel regression is used along with the first extension by combining the Halloween parameter from Jacobsen & Zhang (2013) into the autoregressive model from Kamstra et al. (2003), which results in the following model:

$$\begin{aligned} r_{it} = \beta_0 + \alpha_i + \rho_1 r_{it-1} + \rho_2 r_{it-2} + \beta_{Monday} D_{it}^{Monday} + \beta_{Tax} D_{it}^{Tax} \\ + \beta_{Fall} D_{it}^{Fall} + \beta_{SAD} SAD_{it} + \beta_{Halloween} D_{it}^{Halloween} + \beta_{Expiry} D_{it}^{Expiry} + \varepsilon_{it} \end{aligned} \tag{7}$$

where β_0 indicates the cross-sectional and time-invariant constant, while α_i signifies a time-invariant individual-specific effect in each index. The fixed cross-sectional effect α_i is then tested using the Likelihood Ratio (LR) test in order to check whether it is necessary to be included in the model. The time-specific effect, commonly denoted as λ_t, is not included in the model due to a multicollinearity problem when used alongside with the rest of our variables.

The rest of the model is similar to the original SAD autoregressive model by Kamstra et al. (2003), besides the cross-sectional nature of the panel regression parameters. Returns with up to two lags are used in the whole model in order to avoid excluding the second lagged returns that was present in some of the individual indices. The Halloween effect dummy specified by Bouman & Jacobsen (2002) and the previously defined options expiration days dummy are also included in the model in a cross-sectional form.

5 Results

5.1 Replications

In doing the regressions from the papers by Jacobsen & Zhang (2013) and Kamstra et al. (2003), the obtained results of the replication are mostly in line with the findings in the original papers. Slight differences in the results are detected in the replication of both papers, due to the minor alterations that had to be applied to each respective models as well as the use of different stock indices and time frames. Despite these differences, the main hypothesis of both papers are still supported by the our reported findings.

Monthly and Halloween effects

As mentioned in the methodology section, the monthly effects are examined by doing 12 seperate regressions for every month, each containing only a constant and a dummy variable for each particular month. The monthly and Halloween effect in the returns of S&P500 index from the period of 1965 to 2016 are shown in *Table 3* and *Table 4* respectively.

Table 3: Monthly Seasonal Effects

	β	t-stat	Mean	s.d.
January	0.238	0.373	0.739	5.025
February	-0.544	-0.854	0.022	3.903
March	0.715	1.122	1.176	3.593
April	0.966	1.517	1.406	3.792
May	-0.397	-0.623	0.157	3.703
June	-0.547	-0.859	0.019	3.268
July	-0.233	-0.365	0.307	4.185
August	-0.786	-1.233	-0.199	5.027
September	-1.304	-2.051**	-0.674	4.551
October	0.292	0.458	0.789	6.440
November	0.647	1.016	1.115	4.475
December	0.936	1.484	1.378	3.160
			0.521	4.358

[1] Table 3 shows the results obtained from the regression $r_t = \alpha + \beta_m D_{mt} + \varepsilon_t$, where r_t indicates monthly compounded returns of S&P500 and D_{mt} indicates a dummy variable for each month $m = 1, 2, .., 12$. The table also includes the mean and standard deviation of the S&P500 monthly compounded returns of each month from 1965 to 2016. The last line contains the mean and standard deviation of the monthly compounded returns in the whole sample.
[2] Results are reported in terms of percentages. *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

As seen in the table, most of the individual monthly effects on the are not significant. Returns on September are significantly lower compared to the rest of the year, amounting to 1.3% lower returns during that month. Returns on the rest of the year are considered not significant under the 10% significance level. The returns on April and December are almost significant with 0.97% and 0.94% increased returns respectively, with both months being significant only on a 13% significance level. The results obtained from the regression can be considered in line with the results of Jacobsen & Zhang (2013). In analyzing the UK stock index, Jacobsen & Zhang (2013) obtained comparable values for the period of 1951 to 2009, with months April and December being significantly higher than average, while May, June and September show significantly negative effects on the returns. The difference in May and June may be explained by the different stock indices being used, as well as the difference in time period.

As the months with higher returns are indeed within the Halloween period of November to April as opposed to the lower-return months, the Halloween effect in S&P500 returns is shown in *Table 4*.

Table 4: Halloween seasonal effect

	Mean	**Std. Deviation**	**Positive Returns Percentage**
Winter	0.9741	4.0299	64.82
Summer	0.0665	4.6268	52.29
	$\boldsymbol{\beta}$	**t-stat**	
Halloween	0.9076	2.5899***	

[1] Table 4 shows the results obtained from the regression $r_t = \alpha + \beta_{Halloween} S_t + \varepsilon_t$ where r_t indicates the monthly compounded returns of S&P500, while S_t indicates a dummy variable for the Halloween period. The table also includes the mean, standard deviation and positive returns percentage of the S&P500 monthly compounded returns in the winter (November to April) and summer (May to October) from 1965 to 2016. Positive returns percentage is defined as the number of months that yield returns bigger than zero over the whole sample.
[2] Results are reported in terms of percentages. *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Based on the descriptive statistics of the monthly returns during the winter (November to April) and summer (May to October), monthly returns in the winter have a much higher mean of 0.97% as opposed to the 0.06% mean returns in the summer. Returns in the winter also shows up to 13% more months with positive returns, compared to summer returns. These statistics are in line with the UK index data used by Jacobsen & Zhang (2013), where the winter and summer returns are even more contrasting. As expected, the regression on Halloween effect presented in the last two columns does show a significantly positive value as well. According to the resulting coefficients, investing during the winter period may lead to an extra 0.9% return which supports the "Sell-in-May" and "Come back in September" claims.

SAD Effect

The results of the SAD effect regression for daily index returns located in some of the countries up to 31 December 2000 are shown in *Table 5*. The results of the regression for France, the Netherlands, Germany, Russia and Japan are reported in *Table 11* of the Appendix. The number of lags included in the autoregressive model varies based on each country, ranging from 1 to 2 lags. The number of lags used is determined using a serial correlation Lagrange Multiplier (LM) test on the base linear regression without any lags.

As seen from the table, SAD shows a significant influence in most of the countries listed. The positive coefficient of the SAD in most countries is in line with the findings of Kamstra et al. (2003), where SAD is shown to have a positive effect on daily returns. The SAD effect also varies between countries from different latitudes, with countries in higher latitudes that experience more extreme changes in number of daylight being affected more by SAD compared to countries in the equator or lower latitudes. Although the fall dummy coefficient is not significant for some countries, its strictly negative result for all countries suggests the hypothesis of Kamstra et al. (2003) that investors affected by SAD drift away from risky investments in the fall, leading to lower returns, then returns during the winter which leads to a positive return from SAD.

The coefficient for the Monday dummy shows significant negative results for most coun-

Table 5: SAD regression results on selected indices

	S&P 500 (41°N)		**NASDAQ** (41°N)		**DJI** (41°N)		**EUR** (50°N)		**Canada** (43°N)	
	β	**t-stat**	**β**	**t-stat**	**β**	**t-stat**	**β**	**t-stat**	**β**	**t-stat**
C	0.043	3.140***	0.081	4.800***	0.033	2.318**	0.036	1.276	0.052	2.792***
RETURNS(-1)	10.24	9.636***	15.49	13.63***	8.563	8.095***	-0.566	-0.315	17.62	13.84***
RETURNS(-2)	-3.879	-3.648***	-	-	-4.662	-4.407***	-3.210	-1.787*	-7.169	-5.632***
DMONDAY	-0.094	-3.839***	-0.246	-8.188***	-0.049	-1.941*	-0.007	-0.153	-0.164	-4.998***
DTAX	-0.021	-0.318	0.117	1.421	0.057	0.802	-0.066	-0.472	0.260	3.175***
DFALL	-0.020	-0.889	-0.056	-2.014**	-0.035	-1.482	-0.055	-1.174	-0.073	-2.374**
SAD	0.016	1.733*	0.024	2.163**	0.017	1.826*	0.031	2.361**	0.025	2.238**

	London (51°N)		**Hong Kong** (41°N)		**Indonesia** (6°S)		**Australia** (35°S)		**South Africa** (34°S)	
	β	**t-stat**	**β**	**t-stat**	**β**	**t-stat**	**β**	**t-stat**	**β**	**t-stat**
C	0.062	2.527**	0.090	2.776***	0.092	1.063	0.056	1.730*	0.042	0.457
RETURNS(-1)	6.448	4.240***	6.521	5.309***	6.942	3.288***	5.130	2.394**	11.50	2.772***
RETURNS(-2)	-4.744	-3.120***	-	-	8.557	4.055***	-	-	-	-
DMONDAY	-0.119	-2.799***	-0.185	-3.195***	-0.387	-2.444**	-0.116	-2.022**	0.143	0.869
DTAX	0.137	1.209	-0.108	-0.695	-0.655	-1.641	0.324	2.087**	0.248	0.509
DFALL	-0.058	-1.468	-0.111	-2.088**	-0.015	-0.101	0.005	0.100	-0.154	-0.944
SAD	0.017	1.732*	0.125	2.591***	-0.134	-0.220	0.036	1.343	-0.038	-0.463

[1] Table 5 shows the results obtained from the regression $r_t = \alpha + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{Fall} D_t^{Fall} + \beta_{SAD} SAD_t + \varepsilon_t$ for each index, where r_t indicates the daily returns, r_{t-1} and r_{t-2} the first and second lags of the daily returns. D_t^{Monday}, D_t^{Tax} and D_t^{Fall} indicate the dummy variables for the Monday effect periods, tax-selling periods and fall season periods. SAD_t indicates the scaled hours of night within a given day t between fall and winter. The sample size varies for each index, which includes data up to December 2000. The results of the rest of the countries are reported in *Table 11*.

[2] Results are reported in terms of percentages. *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

tries, suggesting that days following a weekend yield lower returns compared to the rest of the week. Unlike the results from Kamstra et al. (2003), the dummy of tax-loss selling does not show any significant results in most countries other than Canada and Japan. This difference is mostly explained by the difference in time period used for each individual indices, and partially due to the removal of climate condition parameters.

5.2 Extensions

In performing the extensions, we hope to increase the overall accuracy and forecasting power of the original models as well as gaining new insights on the existing literatures. The additional included dummies shows a slight improvement from the original models, but only on a limited number of indices across our sample. The use of panel regression gives a new angle of approach that is not present in the previous literatures, which provides valuable insights on the models seen as a cross-sectional model instead of regular individual time series model.

Halloween dummies and options expiration day dummies inclusion

Regression results of the first extension done by introducing two new variables is reported in *Table 6*, while the rest of the results are reported in the Appendix. The inclusion of the two new variables into the SAD autoregressive model mostly leaves the original parameters unchanged, which signifies the independence between the newly included variables and the initial set of explanatory variables.

Table 6: SAD regression results with additional variables

	S&P 500 (41°N)		**France** (48°N)		**Australia** (35°S)	
	β	**t-stat**	***β***	**t-stat**	***β***	**t-stat**
C	0.038	2.284**	0.053	1.348	-0.033	-0.665
RETURNS(-1)	10.24	9.634***	0.269	0.156	4.828	2.253**
RETURNS(-2)	-3.887	-3.655***	-	-	-	-
DMONDAY	-0.099	-4.005***	-0.149	-2.597***	-0.104	-1.801*
DTAX	-0.022	-0.330	-0.089	-0.584	0.318	2.047**
DFALL	-0.011	-0.460	-0.029	-0.532	-0.030	-0.521
SAD	0.007	0.646	0.006	0.319	-0.007	-0.222
DHALLO	0.030	1.145	0.068	1.117	0.126	2.065**
DEXP	-0.085	-1.823*	-0.183	-1.666*	0.192	1.758*

[1] Table 6 shows the results obtained from the regression $r_t = \alpha + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{Fall} D_t^{Fall} + \beta_{SAD} SAD_t + \beta_{Halloween} D_t^{Halloween} + \beta_{Expiry} D_t^{Expiry} + \varepsilon_t$ for each index, where r_t indicates the daily returns, r_{t-1} and r_{t-2} the first and second lags of the daily returns. D_t^{Monday}, D_t^{Tax}, D_t^{Fall}, $D_t^{Halloween}$ and D_t^{Expiry} indicate the dummy variables for the Monday effect periods, tax-selling periods, fall season periods, Halloween periods and options expiration days respectively. SAD_t indicates the scaled hours of night within a given day t between fall and winter. The sample size varies for each index, which includes data up to December 2000. The results for the rest of the countries are reported in *Table 12*.
[2] Results are reported in terms of percentages. *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

The Halloween effects in this regression are partially absorbed by the fall season dummy, which induces the low significance level of the Halloween dummies, specifically the months November for countries in the Northern Hemisphere and March to April for those in the Southern Hemisphere. As a result, the Halloween dummy variables show significant levels only in the Australian, Russian and Dow Jones indices. The Halloween dummy coefficient shows positive values for countries in the Southern Hemisphere, although the coefficient for the Indonesian index and the South African index does not pass the 10% significance level. The dummy variables for options expiration dates show little significance as well, with only the Australian, French, S&P500 and NASDAQ indices showing significance under the 10% level. The results of the regression signify that weekly expiration days and the Halloween period do not have any meaningful impact on individual stock index returns.

Table 7: Rolling forecast MSPE comparison (*10^{-4})

	DHALLO	**DEXP**	**BASE**	**FULL**
Netherlands	1.384	1.384	1.381	1.387
Australia	0.917	0.916	0.917	0.916
France	1.471	1.470	1.468	1.472
Germany	1.504	1.503	1.501	1.506
Dow Jones	0.920	0.919	0.918	0.921
EUR	1.103	1.103	1.101	1.105
London	1.114	1.116	1.114	1.116
Hong Kong	3.183	3.181	3.174	3.190
Indonesia	9.181	-	9.163	-
Russia	3.970	3.937	3.929	3.978
NASDAQ	1.072	1.070	1.069	1.073
Japan	1.799	1.798	1.797	1.800
S&P500	0.857	0.856	0.855	0.858
Canada	0.807	0.806	0.804	0.808
South Africa	0.386	-	0.386	-

[1] Table 7 shows the MSPE of the rolling regression forecast done with 500 trading days window size and 1 trading day intervals. The first and second columns show the MSPE results for the base model with an additional dummy variable of $D_t^{Halloween}$ and D_t^{Expiry} respectively. The third and fourth columns show the MSPE results for the base model and the full model where both additional dummy variables are included.

Table 7 shows the rolling window forecasts MSPE of each index. As seen from the table, the base model without the additional Halloween and options expiration dummies shows the smallest MSPE in all indices other than Australia. The difference between the highest and the lowest MSPE in these indices ranges only from 0.1% to 0.4%, other than the Russian index where the base model MSPE is 1.2% lower than the full model MSPE. Although it differs by only a very small margin, the MSPE results may suggest that the base model without our two additional dummies is still the best model for forecasting purposes in most cases. This is mainly caused by the fact that in most indices, the Halloween and options expiry dummy does not show any significance, yet their coefficients are relatively high compared to other dummies due to high standard deviations. The addition of these two dummies thus lowers the forecasting accuracy since the MSPE calculation only takes the parameter coefficient into account, regardless of its standard deviation.

In order to compare these models' out-of-sample performances even further, the Diebold-Mariano (DM) test is used. The test compares the forecasting errors of each model adjusted for the sample size. The DM test statistic is then distributed over a normal N(0,1) distribution. The DM test results for S&P500 is reported in *Table 8*, while the rest of the results are reported in *Table 13* of the Appendix.

Table 8: Diebold-Mariano test statistics for S&P 500 index models

	DHALLO	**DEXP**	**BASE**	**FULL**
DHALLO	-	1.080	0.723	0.318
DEXP	-1.080	-	-0.346	-0.814
BASE	-0.723	0.346	-	-0.236
FULL	-0.318	0.814	0.236	-

[1] Table 8 shows the DM test results between the 4 models used. The test statistic is distributed over N(0,1), where the two-tailed 5% significant level is 1.96.

The test results shows that the null hypothesis cannot be rejected under the 5% significance level, indicating that the predictive accuracies of these models are not significantly different. The results from all other indices also suggest no significant difference in forecasting accuracy between the four models, as opposed to what the MSPE values implicate.

Panel Regression

As mentioned in the methodology section, the panel regression is done by adding a fixed cross-sectional effect in the model. The original results of the panel regression is reported in *Table 9*, along with its fixed effects.

Table 9: Panel regression results with fixed effects

	$\boldsymbol{\beta}$	**t-stat**
C	0.000	0.034
RETURNS(-1)	2.765	6.475***
RETURNS(-2)	-1.958	-4.590***
DTAX	-0.109	-2.570**
DMONDAY	0.063	3.669***
DFALL	0.029	1.773*
SAD	-0.004	-0.656
DHALLO	0.026	1.550
DEXP	-0.061	-1.809*
	LR$\sim \chi^2(14)$	**Prob.**
Cross-section LR-test	10.912325	0.6929

[1] Table 9 shows the results obtained from the regression $r_{it} = \beta_0 + \alpha_i + \rho_1 r_{it-1} + \rho_2 r_{it-2} + \beta_{Monday} D_{it}^{Monday} + \beta_{Tax} D_{it}^{Tax} + \beta_{Fall} D_{it}^{Fall} + \beta_{SAD} SAD_{it} + \beta_{Halloween} D_{it}^{Halloween} + \beta_{Expiry} D_{it}^{Expiry} + \varepsilon_{it}$ for each index, where r_{it} indicates the daily returns for index i, r_{it-1} and r_{it-2} the first and second lags of the daily returns.α_i indicates the index-specific fixed effect of the model. D_{it}^{Monday}, D_{it}^{Tax}, D_{it}^{Fall}, $D_{it}^{Halloween}$ and D_{it}^{Expiry} indicate the dummy variables for the Monday effect periods, tax-selling periods, fall season periods, Halloween periods and options expiration days respectively. SAD_{it} indicates the scaled hours of night for index i within a given day t between fall and winter. The sample size varies for each index, which includes data up to December 2016.

[2] Results are reported in terms of percentages. *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Index	$\boldsymbol{\alpha_i}$
Netherlands	-0.021
Australia	-0.009
France	-0.015
Germany	-0.004
Dow Jones	-0.009
EUR	-0.017
London	-0.030
Hong Kong	0.004
Indonesia	0.054
Russia	0.051
NASDAQ	0.001
Japan	-0.000
S&P500	-0.012
Canada	-0.006
South Africa	0.015

[3] Table 9 shows the different fixed effects of each index α_i, as well as the LR-test for fixed effect redundance. Based on the test statistic, the null hypothesis of redundant fixed effects cannot be rejected under the 5% significance level.

As the redundant fixed effect LR-test is taken, the high probability value of the test (0.692) urges us to not reject the null hypothesis where the fixed effects are considered redundant. A new panel regression model is then constructed by omitting the fixed effect from the regression. The results of the altered model is reported in *Table 10*.

Table 10: Panel regression results without fixed effects

	β	t-stat
C	0.000	0.025
RETURNS(-1)	2.785	6.523***
RETURNS(-2)	-1.938	-4.545***
DTAX	-0.106	-2.518**
DMONDAY	0.063	3.668***
DFALL	0.030	1.843*
SAD	-0.007	-1.209
DHALLO	0.029	1.831*
DEXP	-0.066	-1.958*

[1] Table 10 shows the results obtained from the regression $r_{it} = \beta_0 + \rho_1 r_{it-1} + \rho_2 r_{it-2} + \beta_{Monday} D_{it}^{Monday} + \beta_{Tax} D_{it}^{Tax} + \beta_{Fall} D_{it}^{Fall} + \beta_{SAD} SAD_{it} + \beta_{Halloween} D_{it}^{Halloween} + \beta_{Expiry} D_{it}^{Expiry} + \varepsilon_{it}$ for each index, where r_{it} indicates the daily returns for index i, r_{it-1} and r_{it-2} the first and second lags of the daily returns. D_{it}^{Monday}, D_{it}^{Tax}, D_{it}^{Fall}, $D_{it}^{Halloween}$ and D_{it}^{Expiry} indicate the dummy variables for the Monday effect periods, tax-selling periods, fall season periods, Halloween periods and options expiration days respectively. SAD_{it} indicates the scaled hours of night for index i within a given day t between fall and winter. The sample size varies for each index, which includes data up to December 2016.
[2] Results are reported in terms of percentages. *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

As seen from the table, most of the estimated parameters are significant, other than SAD. Due to the large sample size of the panel data as a whole, significant parameters are easier to be obtained compared to the individual regressions. The SAD variable, however, cannot be considered significant under the 10% level. The main reason behind this result is due to the inclusion of all 15 indices in the regression, yet more recent time series of each individual index. As seen from the SAD model replication results, SAD does not show significant results in some countries, and especially those in the Southern Hemisphere. The replication results also uses only data up to December 2000, which is almost disjointed with the 1998 to 2016 data used in the panel regression. The same SAD replication model using data up to December 2016 do show a lower coefficient and significance of the SAD effect, which suggests that the SAD effect has less presence in the period of 2000 to 2016. This indicates that when taken as an aggregate of the 15 selected indices, SAD does not have enough impact on the stock returns in order to be considered a significant factor during the 1998-2016 period. On the other hand, the dummies on Halloween effect and options expiration days shows significance on the 10% level, as opposed to the previous individual regressions. The cause of sudden change on significance level in both dummy variables are mainly similar to that of the SAD variable, where an aggregated estimation between all 15 indices and a different timeframe being used are the main drivers behind the different results.

6 Conclusion

As we analyze the seasonality pattern in stock index returns, an apparent yet barely significant seasonal effects can be derived. These patterns widely varies among each country, as a seasonal effect may be more present in a particular country than in others while essentially disappearing in another. Based on the noticeable findings, a trading strategy may be constructed where the unsystematic risk may be reduced by taking these seasonal effects into account.

As seen from the results section, monthly seasonal effects are barely significant on the monthly index returns. Considering the results from Jacobsen & Zhang (2013), the insignificant findings are hardly surprising due to the low significance of calendar month effects over the years. The calendar months effects are also relatively easier for most investors to observe, which induces them to take advantage of it and thus continuously diminishing any significant effect of any calendar month. Based on the replication findings, it may be more beneficial for investors to focus on other seasonal effects instead, such as the Monday effect, tax-loss selling periods and the fall season where relatively more meaningful significance can be found depending on the country. It is also helpful for investors to pay attention to the hours of nights in a particular country, especially Western countries in general where longer hours of nights leads to a slightly higher return.

The further examination of these effects incorporated in the extensions provides us with a more in-depth perception of each seasonal effects. The Halloween dummy introduced by Bouman & Jacobsen (2002) shows only a little amount of significance when corrected for the fall seasonal effect and all the other variables, which is a good suggestion to not rely on the Halloween effect too much as suggested by the first replication results where the Halloween effect shows a substantial significance. The options expiration days does not show any significant effect in most indices, but on the few indices such as NASDAQ and CAC 40, these days do show lower returns relative to the rest of the month. Considering the fact that the options expiration day only occurs once a month, it may be tougher to utilize on this seasonal effect as opposed to other effects that may take place more frequently and continuously. The panel regression allows us to infer that all the seasonal effects we have been analyzing do have a significant effect across the globe, except the SAD effect. The increase in number of observations from various countries allows a more robust estimation, at the price of losing the index-specific characteristics. In constructing a portfolio, however, it may be better to utilize the index-specific estimations as the panel regression serves only to give a big picture on the seasonality pattern. The panel regression result depicts the behavior of a portfolio that is constructed with all the indices with the exact same weights and positions, although it is not necessarily the most efficient portfolio. With all the differences among the countries in mind, we believe that it is beneficial for investors to take the seasonal effects into account when constructing their portfolio.

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8 Appendix

Table 11: SAD Regression Results on selected indices

	France (48°N)		**Netherlands** (52°N)		**Germany** (39°N)		**Russia** (55°N)		**Japan** (35°N)	
	$\boldsymbol{\beta}$	**t-stat**	$\boldsymbol{\beta}$	**t-stat**	$\boldsymbol{\beta}$	**t-stat**	$\boldsymbol{\beta}$	**t-stat**	$\boldsymbol{\beta}$	**t-stat**
C	0.066	2.022**	0.082	3.122***	0.068	3.342***	-0.242	-0.978	0.043	1.513
RETURNS(-1)	0.313	0.181	-3.477	-2.345**	1.282	1.112	6.888	1.964**	1.204	1.053
RETURNS(-2)	-	-	-2.221	-1.497	-3.618	-3.136***	-	-	-2.367	-2.072**
DMONDAY	-0.140	-2.441**	-0.089	-1.931*	-0.130	-3.634***	0.507	1.199	-0.004	-0.086
DTAX	-0.092	-0.599	0.223	1.734*	0.126	1.284	0.176	0.169	-0.654	-4.733***
DFALL	-0.051	-0.976	-0.065	-1.517	-0.044	-1.331	-0.059	-0.160	-0.043	-0.912
SAD	0.020	1.327	0.015	1.353	0.016	1.639	0.079	0.919	0.029	1.237

[1] Table 11 shows the results obtained from the regression $r_t = \alpha + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{Fall} D_t^{Fall} + \beta_{SAD} SAD_t + \varepsilon_t$ for each index, where r_t indicates the daily returns, r_{t-1} and r_{t-2} the first and second lags of the daily returns. D_t^{Monday}, D_t^{Tax} and D_t^{Fall} indicate the dummy variables for the Monday effect periods, tax-selling periods and fall season periods. SAD_t indicates the scaled hours of night within a given day t between fall and winter. The sample size varies for each index, which includes data up to December 2000.

[2] Results are reported in terms of percentages. *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Table 12: SAD regression results with additional variables

	London (51°N)		**Hong Kong** (41°N)		**Indonesia** (6°S)		**EUR** (50°N)		**South Africa** (34°S)		**Canada** (43°N)	
	β	**t-stat**	**β**	**t-stat**	**β**	**t-stat**	**β**	**t-stat**	**β**	**t-stat**	**β**	**t-stat**
C	0.054	1.862*	0.090	2.330**	0.037	0.288	0.031	0.899	0.016	0.114	0.052	2.329**
RETURNS(-1)	6.464	4.249***	6.511	5.299***	6.934	3.283***	-0.568	-0.316	11.48	2.762***	17.62	13.84***
RETURNS(-2)	-4.750	-3.122***	-	-	8.544	4.049***	-3.259	-1.814*	-	-	-7.170	-5.629***
DMONDAY	-0.125	-2.917***	-0.188	-3.216***	-0.386	-2.435**	-0.012	-0.246	0.144	0.870	-0.166	-5.012***
DTAX	0.099	0.842	-0.114	-0.728	-0.695	-1.716*	-0.067	-0.474	0.254	0.518	0.258	3.154***
DFALL	-0.044	-1.074	-0.113	-2.020**	-0.025	-0.169	-0.046	-0.924	-0.164	-0.965	-0.072	-2.216**
SAD	0.008	0.626	0.128	2.043**	-0.402	-0.526	0.025	1.470	-0.052	-0.497	0.024	1.677*
DHALLO	0.046	0.987	-0.004	-0.064	0.095	0.583	0.030	0.570	0.037	0.216	0.003	0.093
DEXP	-0.105	-1.296	0.040	0.372	-	-	-0.085	-0.869	-	-	-0.027	-0.433

	NASDAQ (41°N)		**Netherlands** (52°N)		**Germany** (39°N)		**Russia** (55°N)		**Japan** (35°N)		**DJI** (41°N)	
	β	**t-stat**	**β**	**t-stat**	**β**	**t-stat**	**β**	**t-stat**	**β**	**t-stat**	**β**	**t-stat**
C	0.084	4.127***	0.065	2.063**	0.061	2.504**	-0.486	-1.641	0.029	0.867	0.020	1.143
RETURNS(-1)	15.57	13.70***	-3.524	-2.376**	1.263	1.095	6.476	1.843*	1.195	1.046	8.532	8.066***
RETURNS(-2)	-	-	-2.282	-1.537	-3.615	-3.133***	-	-	-2.396	-2.097**	-4.705	-4.447***
DMONDAY	-0.254	-8.419***	-0.092	-1.982**	-0.133	-3.702***	0.487	1.145	-0.010	-0.207	-0.053	-2.086**
DTAX	0.111	1.344	0.228	1.773*	0.127	1.285	0.237	0.227	-0.645	-4.660***	0.059	0.838
DFALL	-0.051	-1.739*	-0.046	-1.017	-0.035	-0.995	0.187	0.468	-0.025	-0.512	-0.019	-0.769
SAD	0.020	1.403	0.003	0.246	0.010	0.792	-0.043	-0.382	0.008	0.286	0.003	0.260
DHALLO	0.015	0.496	0.062	1.255	0.029	0.773	0.767	1.694*	0.057	1.074	0.051	1.892*
DEXP	-0.146	-2.560**	-0.064	-0.728	-0.063	-0.929	-0.342	-0.432	-0.103	-1.086	-0.074	-1.532

[1] Table 12 shows the results obtained from the regression $r_t = \alpha + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{Fall} D_t^{Fall} + \beta_{SAD} SAD_t + \beta_{Halloween} D_t^{Halloween} + \beta_{Expiry} D_t^{Expiry} + \varepsilon_t$ for each index, where r_t indicates the daily returns, r_{t-1} and r_{t-2} the first and second lags of the daily returns. D_t^{Monday}, D_t^{Tax}, D_t^{Fall}, $D_t^{Halloween}$ and D_t^{Expiry} indicate the dummy variables for the Monday effect periods, tax-selling periods, fall season periods, Halloween periods and options expiration days respectively. SAD_t indicates the scaled hours of night within a given day t between fall and winter. The sample size varies for each index, which includes data up to December 2000.

[2] Results are reported in terms of percentages. *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Table 13: Diebold-Mariano test stastic results

Netherlands		**DHALLO**	**DEXP**	**BASE**	**FULL**
	DHALLO	-	-1.154	-0.934	-1.459
	DEXP	1.154	-	1.359	0.936
	BASE	0.934	-1.359	-	0.701
	FULL	1.459	-0.936	-0.701	-
Australia		**DHALLO**	**DEXP**	**BASE**	**FULL**
	DHALLO	-	1.099	1.113	-0.876
	DEXP	-1.099	-	0.802	-1.131
	BASE	-1.113	-0.802	-	-1.105
	FULL	0.876	1.131	1.105	-
France		**DHALLO**	**DEXP**	**BASE**	**FULL**
	DHALLO	-	0.678	1.230	-0.120
	DEXP	-0.678	-	0.125	-1.226
	BASE	-1.230	-0.125	-	-1.259
	FULL	0.120	1.226	1.259	-
Germany		**DHALLO**	**DEXP**	**BASE**	**FULL**
	DHALLO	-	0.562	0.882	-0.210
	DEXP	-0.562	-	0.313	-0.820
	BASE	-0.882	-0.313	-	-0.960
	FULL	0.210	0.820	0.960	-
Dow Jones		**DHALLO**	**DEXP**	**BASE**	**FULL**
	DHALLO	-	0.790	0.272	0.854
	DEXP	-0.790	-	-0.913	-0.374
	BASE	-0.272	0.913	-	0.268
	FULL	-0.854	0.374	-0.268	-
EUR		**DHALLO**	**DEXP**	**BASE**	**FULL**
	DHALLO	-	1.093	1.517	-0.684
	DEXP	-1.093	-	0.690	-1.516
	BASE	-1.517	-0.690	-	-1.740
	FULL	0.684	1.516	1.740	-
London		**DHALLO**	**DEXP**	**BASE**	**FULL**
	DHALLO	-	-1.590	-1.626	-0.613
	DEXP	1.590	-	0.679	1.623
	BASE	1.626	-0.679	-	1.658
	FULL	0.613	-1.623	-1.658	-

Hong Kong		DHALLO	DEXP	BASE	FULL
	DHALLO	-	1.258	1.346	-1.104
	DEXP	-1.258	-	1.065	-1.346
	BASE	-1.346	-1.065	-	-1.392
	FULL	1.104	1.346	1.392	-
Indonesia		**DHALLO**	**DEXP**	**BASE**	**FULL**
	DHALLO	-	-	-0.889	-
	DEXP	-	-	-	-
	BASE	0.889	-	-	-
	FULL	-	-	-	-
Russia		**DHALLO**	**DEXP**	**BASE**	**FULL**
	DHALLO	-	0.718	0.704	-0.060
	DEXP	-0.718	-	-0.060	-0.720
	BASE	-0.704	0.060	-	-0.700
	FULL	0.060	0.720	0.700	-
NASDAQ		**DHALLO**	**DEXP**	**BASE**	**FULL**
	DHALLO	-	0.718	0.704	-0.060
	DEXP	-0.718	-	-0.060	-0.720
	BASE	-0.704	0.060	-	-0.700
	FULL	0.060	0.720	0.700	-
Japan		**DHALLO**	**DEXP**	**BASE**	**FULL**
	DHALLO	-	-0.623	-0.911	1.139
	DEXP	0.623	-	-1.217	0.889
	BASE	0.911	1.217	-	1.076
	FULL	-1.139	-0.889	-1.076	-
Canada		**DHALLO**	**DEXP**	**BASE**	**FULL**
	DHALLO	-	-1.311	-1.267	-1.173
	DEXP	1.311	-	1.121	1.270
	BASE	1.267	-1.121	-	1.202
	FULL	1.173	-1.270	-1.202	-
South Africa		**DHALLO**	**DEXP**	**BASE**	**FULL**
	DHALLO	-	-	-0.233	-
	DEXP	-	-	-	-
	BASE	0.233	-	-	-
	FULL	-	-	-	-

[1] Table 13 shows the DM test results between the 4 models used. The test statistic is distributed over N(0,1), where the two-tailed 5% significant level is 1.96.