# MULTI-NATIONAL EVIDENCE ON CALENDAR PATTERNS IN STOCK RETURNS: AN EMPIRICAL CASE STUDY ON INVESTMENT STRATEGY AND THE HALLOWEEN EFFECT

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**ABSTRACT**

*This research tries to find evidence for the Halloween effect by presenting an assessment of the profitability of the "Sell in May, and go away" investment strategy associated with this phenomenon. We present significant proof of the existence of the Halloween effect; it was observed in 29 of the 31 countries under study. There appears to be a difference in the seasonal returns between developed and emerging markets. Attention is also paid to the Halloween effect at the industry level. Here, a comparison between the "Sell in May, and go away" investment strategy and the buy-and-hold strategy proves the first to be superior.*

**JEL:** G110, G120

**KEYWORDS:** January Effect, Investment Decisions

## INTRODUCTION

Recent studies have shown the existence of seasonal patterns in industry returns. More specifically, stock market returns tend to be significantly lower during the summer period (May up to and including October) than during the winter period (November up to and including April) (Bouman and Jakobsen, 2002). This irregularity or anomaly is also known as the Halloween effect, or the "Sell in May, and go away" strategy.

The "Sell in May, and go away" investment strategy, associated with the Halloween effect, means that investors sell their stocks in May - because of the supposedly lower returns in the summer period - and invest their proceeds in risk-free assets, such as short-term Treasury bonds. They will hold on to these risk-free assets until the Halloween ('October 31') and then sell them, investing the returns again in their market portfolio. The very existence of exploitable seasonal patterns is in contradistinction with the theory of efficient markets, which makes the Halloween effect a remarkable phenomenon. This paper belongs to the body of literature which questions the efficiency of the stock markets by showing that certain stock returns patterns are related to particular calendar time periods, such as the January effect, the Monday effect and the turn-of-the-month effect. There are two opposing views on the issues of market efficiency and the Halloween effect. The one view, advocated by Bouman and Jakobsen (2002), supports the latter's existence. The debate on the Halloween effect among different authors is therefore concerned with a much broader issue, namely that of the perpetuation of the existence of the efficient market theory on the one hand, or its very extinction on the other. In our research we have attempted to find out whether there is any evidence for the Halloween effect and whether the "Sell in May, and go away" investment strategy associated with this phenomenon is profitable. In order to find out which vision concerning the seasonal patterns in stock returns is the most reliable we combined the views presented by both Jakobsen and Bouman (2002) and Maberly and Pierce (2004).

In order to shed light on the relationship between seasonal patterns and stock exchange returns we investigated 31 countries by comparing the differences between winter and summer returns and testing these differences statistically by means of a regression analysis. The regression analysis was extended by adding control variables in the same manner it was done in the 2004 Maberly and Pierce paper. The control variables consisted of the January effect and data outliers.

After assessing the evidence for the Halloween effect we looked at the impact of the January effect on this phenomenon. The January effect can be described as the tendency of stocks to rise between the last day of December and the first week of January (Haug and Hirschey, 2006). This implies that the January effect causes greater differences between the seasonal returns, which (partially) explains the Halloween effect.

Data outliers formed the other control variable used. We applied two control variables: the October 1987 stock market crash and the August 1998 Ruble crisis in which the Russian government announced moratorium on debt repayment (Henry and Nixon, 1998). Because both of the outliers represent summer periods they contributed to the widening of the seasonal gap and hence corroborated the existence of the Halloween effect. When, however, these data outliers were controlled for, the gap between the seasons decreased and thus also the significance of the Halloween effect, which meant that in the case of the US the Halloween effect disappeared (Maberly and Pierce, 2004).

The first question we tried to answer was whether the winter returns were significantly larger than the summer returns once the January effect and the data outliers were taken into account. Since we chose to use the perspective of the efficient market theory we adjusted our expectations accordingly. We expected to find evidence for neither the Halloween effect nor for the January effect. We did expect that controlling for the data outliers would increase the summer mean returns and hence decrease the Halloween effect, if it existed.

The second question dealt with determining possible differences in the seasonal returns between mature and emerging markets. Emerging markets are less integrated than mature markets, which means that the first have less co-movement, making them more unreliable.

The third question was concerned with finding evidence for the Halloween effect at the industry level. Also here we started from the theory of efficient markets, assuming to find no evidence for the Halloween effect at the industry level.

The final and most important question in this study pertains to whether the “Sell in May, and go away” investment strategy is more profitable than the simple buy-and-hold strategy. Can investors make money by applying the Halloween effect theory? Using once again the efficient market theory as our point of departure, we expected that the simple buy-and-hold strategy would be more profitable because of the lack of transaction costs.

The Halloween effect is an interesting topic for several reasons. First of all, it has considerable economic significance. If the Halloween effect truly exists to a significant degree, it could change people’s investing behaviour. The simple buy-and-hold strategy would then perish and make place for the “Sell in May, and go away” investing strategy. Second, the Halloween effect is interesting because although it has been detected and identified, it still exists. So far neither the investors nor the markets have been able to adjust themselves adequately to this phenomenon. Thirdly, the Halloween effect is, unlike other calendar effects, an exploitable anomaly in that it is associated with much lower transaction costs than, for example, the Weekend effect or the Turn of the month effect.

Fourthly, by examining the seasonal returns of countries on different continents we could establish to what degree the markets are integrated and how this integration evolves over time.

Finally, this study may unravel the Halloween puzzle by presenting another question: if the Halloween effect exists, how can this phenomenon be explained? Why are there differences in seasonal returns and why do they exist? As stated earlier, the Halloween puzzle is closely related to the efficiency of the markets and their ability to adjust returns on the basis of available information.

This paper is arranged as follows. First of all the literature review is presented. Section I explains the Halloween puzzle, the methodology and data used. Section II presents the methodology and results obtained. The section describes some general trends in the data. In section III the results are discussed and possible explanations for the Halloween effect are given. Finally, in section IV we establish a link between the results obtained and their possible explanations. This is also the concluding section.

## LITERATURE REVIEW

In the 2002 paper Bouman and Jakobsen (2002) examined 37 countries and found evidence for the Halloween effect in 36 of them. The other view, supported by Maberly and Pierce (2004), rejects the existence of an exploitable anomaly such as the Halloween effect. In their 2004 paper they re-examine the Bouman and Jakobsen (2002) study, concluding that the Halloween effect as it occurred in the United States of America disappeared after certain adjustments had been made. These adjustments pertained to the influence exerted by the January effect and data outliers on the stock returns. This finding refutes the existence of the Halloween effect as an exploitable anomaly and reconfirms the theory of efficient markets.

These studies add to the literature which presents evidence for higher stock returns during periods which are not directly linked to financial events, such as the seasons of the year [Hirshleifer and Shumway (2003), Kamstra, Kramer and Levi (2003)], Democratic/Republic Presidency [Santa-Clara and Valkanov (2003)] and Congress in Session [Ferguson and Witte (2006)].

The paper of De Santis and Imrohoroglu (1997) states that emerging markets have a higher volatility associated with higher returns in comparison with mature markets. On the basis of this information we could expect to find bigger differences in seasonal returns in the mature markets than in the emerging markets.

In their 2003 paper Kamstra, Kramer, and Levi link Seasonal Affective Disorder (SAD) with risk aversion (Kamstra et. al., 2003). It appears that once people’s depression levels increase they become less inclined to subject themselves to risk.

As stated earlier, recent evidence shows the existence of seasonal patterns in industry returns. And although differences between seasons indeed appear to be significant in some markets, we should not be overly alarmed by this finding. It does question, however, the efficiency of these markets. According to the efficient market theory it is not possible for investors to benefit from market timing activities such as the Halloween effect, because financial markets are supposed to respond to all information generally known. In this way it should not be possible for companies to outperform the market by repeatedly playing the same “trick” or using a market trading mechanism, since the market accounts for these factors by incorporating the whole spectrum of market information so that companies’ returns are automatically adjusted. If one assumes that markets are indeed efficient, this means that the probability of finding higher winter than summer returns is 50%. The reason why the Halloween effect is a puzzle is because in more than 50% of the cases the winter returns appear to be higher than the summer returns.

## DATA AND METHODOLOGY

In order to test whether the Halloween effect actually exists we investigated for 31 countries whether the winter returns were indeed significantly higher than the summer returns. A regression technique resembling the simple-mean test was used to check whether seasonal differences were in fact present and significant. The regression is represented by:

$$R_t = \mu + \alpha_1 S_t + \varepsilon_t \tag{1}$$

Where:

- $R_t$ is the dependent variable which stands for monthly compounded stock returns.
- $S_t$ represents the season dummy and equals 1 for the winter period and 0 for the summer period. $\mu$ Is a constant and $\varepsilon_t$ is the usual error term.

This is the core regression used. During the remainder of the paper it is extended by other (control) variables. Please note that when the dummy variable S takes the value 0 for the summer period, the whole regression is reduced to:

$$R_t = \mu \tag{2}$$

which means that $\mu$ indicates the summer stock market returns. When the season dummy equals 1 for the winter period, the regression becomes:

$$R_t = \mu + \alpha_1 \tag{3}$$

which means that $\mu + \alpha_1$ represents the winter returns. When $\alpha_1$ is positive and significant, the null hypothesis can be rejected. A positive and significant $\alpha_1$ equals a significant difference between the summer and winter stock market returns.

The regression technique resembles a simple mean test according to which one tries to find out whether there is a significant difference among the groups. The advantage of the regression is that the formula can be very easily extended by adding other variables which are required to test the rest of the hypotheses.

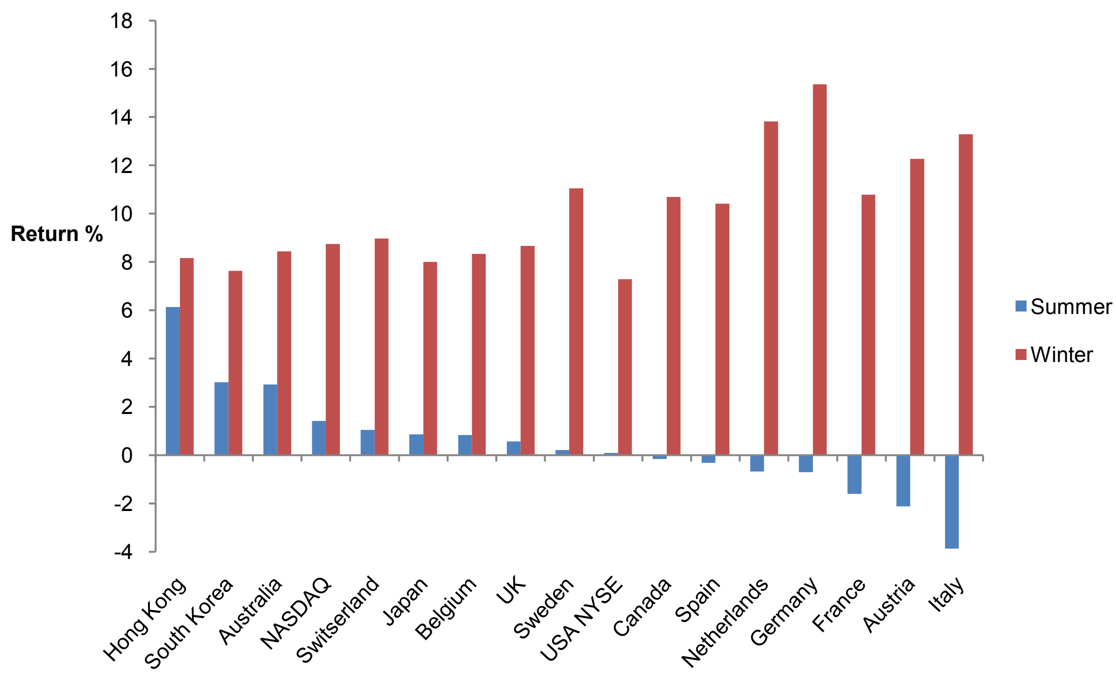
We used the monthly stock returns of value-weighted stock markets. For this research 17 developed and 14 developing countries were examined, amounting to a total of 31 countries. The countries investigated are: Australia, Austria, Bangladesh, Belgium, Canada, Chile, China, Czech Republic, France, Germany, Hong Kong, Hungary, India, Italy, Japan, Malaysia, Mexico, Netherlands, Poland, Portugal, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Turkey, United Kingdom and the United States of America.

The US is the only country represented by two stock exchanges: the New York Stock Exchange and NASDAQ. This is because NASDAQ is one of the world’s largest stock exchanges which could simply not be neglected in the research. There are two major reasons why so many emerging markets were included in the research. First of all, adding these markets provided us with a clearer picture of the Halloween effect. Secondly, this approach enabled us to make a comparison of the seasonal returns of the mature markets with those of the emerging markets.

## RESULTS

Figure 1 shows the average stock market returns for the developed countries in the summer and winter periods. Firstly, we can see that in all 17 countries the winter returns are higher than the summer returns. According to the efficient market theory the chance of such a finding is 0.000763%. The probability was calculated as follows: 0.5^17. This difference between seasons is rather pronounced in all countries, except in Hong Kong, South Korea, and Australia. Another interesting finding is that in most countries the average summer returns are around 0%.

Figure 1: Average Winter and Summer Returns in Developed Markets

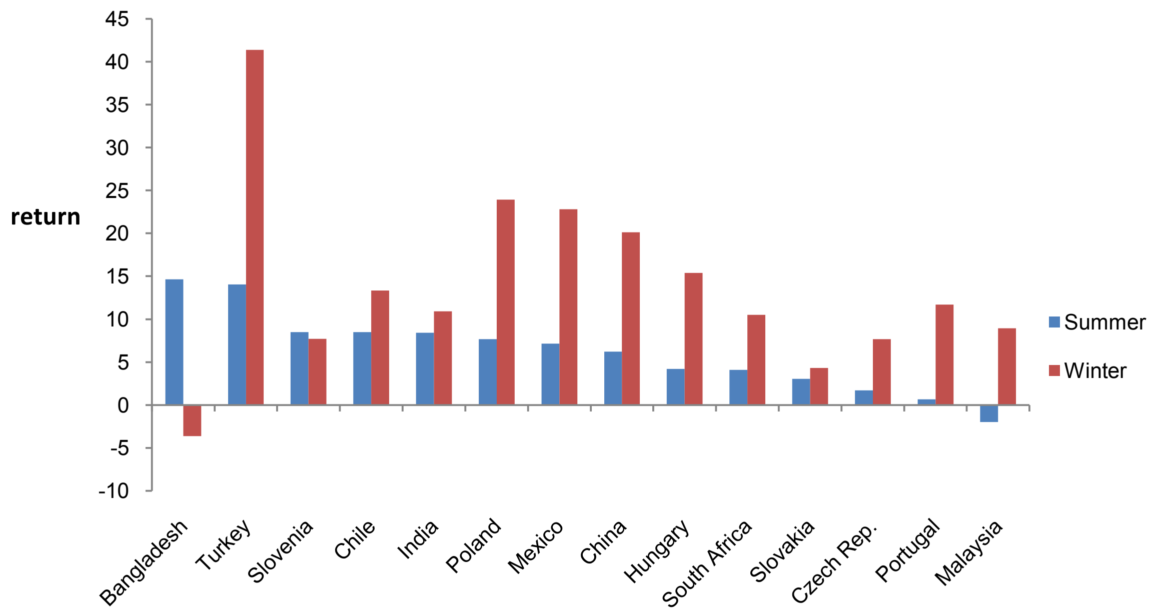



*Average winter and summer returns in developed markets expressed as a percentage.*

Figure 2 presents the results for the emerging markets. Here 12 out of the 14 countries show higher winter than summer returns. The probability is rather small, namely 0.56%. The probability was calculated as follows: 0.5^17. The probability was calculated as follows: 0.5^14*(NcR 14-2). An interesting observation is that only one of the 14 emerging markets shows negative summer returns, while no less than17 of the developed markets show this result. Although at this point some preliminary statements about the economic significance of these results could certainly be made, the prominent question is, however, whether they are also statistically significant.

As we can see in table 1, in 16 of the 31 countries the winter returns are significantly higher than the summer returns; here the significance level is 10%. In eight countries the "Sell in May, and go away" effect seems to be very strong on a 1% significance level (see table 1). This finding supports the existence of seasonal differences. However, it is interesting to note that all eight countries exhibiting a strong "Sell in May, and go away" effect are developed countries.

Figure 2: Returns in Winter and Summer in Emerging Markets




*Average returns during the winter period (November-April) and the summer period (May-October) in emerging markets expressed as*

In 29 of the 31 countries the winter returns are higher than the summer returns, while this difference is actually significant in 16 of these countries. So far the results do in fact provide support for the existence of the Halloween effect. The next step is now to include the control variable to check for the effect in countries where the winter returns are higher than the summer returns, and to determine the significance of these results.

First we investigate the effect of controlling for the January effect on the gap between the winter and summer returns. In January, especially in the first week of this month, stocks show a tendency to rise in price (the so-called January effect). As a result the winter returns are higher, since January falls in the winter period. By controlling for the January effect we could obtain a clearer picture of the winter returns, enabling us to make a more reliable comparison between the winter and the summer returns. The first column of table 2 shows the mean winter returns prior to the January effect adjustment, and the second column represents the adjusted winter returns.

The third column indicates that the effect of controlling for the excessive January returns is negative for 23 of the 31 countries. For 14 of the 17 developed markets and 9 of the 14 emerging markets the adjusted winter returns appear to be lower than the non-adjusted winter returns. So the next question is how controlling for the January effect influences the significance of the "Sell in May, and go away" effect.

Table 1: Results for All Stock Exchanges Investigated

| Country | Number of Observations | Mean | Standard Deviation | Season Differences | T-value of the Halloween Effect |
|---|---|---|---|---|---|
| Australia | 180 | 0.62 | 3.40 | 4.13 | 1.148 |
| Austria | 264 | 0.70 | 6.76 | 14.4 | 2.584 *** |
| Bangladesh | 216 | 0.69 | 13.24 | -18.28 | -1.495 |
| Belgium | 216 | 0.31 | 4.80 | 7.50 | 1.936 * |
| Canada | 468 | 0.53 | 4.59 | 7.38 | 2.697 *** |
| Chile | 216 | 1.69 | 6.49 | 4.86 | 0.739 |
| China | 204 | 1.82 | 19.25 | 13.90 | 0.205 |
| Czech Rep. | 156 | 0.38 | 6.69 | -2.96 | 0.89 |
| France | 252 | 0.61 | 5.76 | 12.40 | 2.641 *** |
| Germany | 516 | 0.54 | 5.53 | 8.54 | 2.612*** |
| Hong Kong | 516 | 1.09 | 9.72 | 2.04 | 0.185 |
| Hungary | 204 | 1.60 | 10.21 | 11.21 | 1.377 |
| India | 252 | 1.51 | 9.00 | 2.49 | 0.201 |
| Italy | 276 | 0.73 | 6.71 | 17.07 | 3.619 *** |
| Japan | 684 | 0.71 | 5.13 | 7.14 | 2.902 *** |
| Malaysia | 336 | 0.53 | 8.42 | 10.92 | 1.895 * |
| Mexico | 240 | 2.39 | 8.63 | 15.68 | 1.286 |
| Netherlands | 300 | 0.78 | 5.74 | 11.34 | 2.709 *** |
| Poland | 192 | 2.15 | 13.65 | 16.28 | 0.683 |
| Portugal | 180 | 0.67 | 6.29 | 11.04 | 1.897 * |
| Slovakia | 156 | 3.76 | 6.69 | 1.30 | 0.042 |
| Slovenia | 168 | 1.24 | 6.66 | -3.92 | -0.037 |
| South Africa | 144 | 1.00 | 6.23 | 6.42 | 0.844 |
| South Korea | 396 | 0.85 | 7.71 | 4.61 | 0.996 |
| Spain | 252 | 0.71 | 6.47 | 10.73 | 1.915 * |
| Sweden | 264 | 0.91 | 6,79 | 10.84 | 2.199 ** |
| Switserland | 192 | 0.70 | 4.84 | 7.92 | 1.764 * |
| Turkey | 240 | 3.82 | 17.88 | 27.35 | 1.722 * |
| United Kingdom | 348 | 0.72 | 4.92 | 8.11 | 2.123 ** |
| United States (NYSE) | 684 | 0.59 | 4.09 | 7.19 | 3.695 *** |
| United States (NASDAQ) | 300 | 0.84 | 8.84 | 7.31 | 1.285 |

*Notes: This table shows the results for all the 31 stock exchanges (calculated on the basis of value weighted index returns. The number of observations stands for the number of months used per country. For all countries the last month observed was December 2007. Mean stands for monthly mean returns expressed as percentages. This also applies to the standard deviation (on a monthly basis and expressed as percentages). Season difference stands for the difference between the winter returns and the summer returns, expressed as percentages. Finally, the last column presents the associated t-values per country. The addition * means that the t-values are significant at a 10% significance level, ** at a 5% significance level and *** at a 1% significance level.*

The January effect is positively significant in eight of the 31 countries, in five countries at a 10% significance level, and in three countries at a 1% significance level. The positive relationship between the monthly mean returns and the January dummy means that controlling for the January effect results in lower winter returns. These lower winter returns will, in turn, lead to a smaller winter-summer gap, which decreases the impact of the "Sell in May, and go away" effect. When looking at the season dummy, the January effect is significant in 13 of the 31 countries, which is a reduction of three countries (see table 1 and 3).

Table 2: Effect of the January Dummy on the Winter Returns

| Country | Mean Winter | Mean Winter January Adjusted | January Effect | Mean Summer |
|---|---|---|---|---|
| Australia | 7.06 | 8.65 | 1.59 | 2.93 |
| Austria | 12.27 | 6.75 | **-5.52** | -2.13 |
| Bangladesh | -3.65 | 9.93 | 13.58 | 14.63 |
| Belgium | 8.33 | 6.69 | **-1.64** | -0.83 |
| Canada | 7.21 | 5.14 | **-2.07** | -0.16 |
| Chile | 13.34 | 18.64 | 5.30 | 8.48 |
| China | 20.11 | 19.58 | **-3.81** | 6.21 |
| Czech Rep. | 7.67 | 6.46 | **-1.21** | 1.71 |
| France | 10.79 | 7,54 | **-3.25** | -1.61 |
| Germany | 7.84 | 4.58 | **-3.26** | -0.70 |
| Hong Kong | 8.16 | 10.01 | 1.85 | 6.13 |
| Hungary | 15.40 | 12.68 | **-2.72** | 4.19 |
| India | 10.91 | 17.92 | 7.01 | 8.42 |
| Italy | 13.29 | 9.54 | **-3.75** | -3.78 |
| Japan | 8.00 | 5.88 | **-2.12** | 0.86 |
| Malaysia | 8.94 | 4.72 | **-4.22** | -1.98 |
| Mexico | 22.81 | 24.21 | 1.40 | 7.13 |
| Netherlands | 10.66 | 8.63 | **-2.03** | -0.68 |
| Poland | 23.94 | 21.18 | **-2.76** | 7.66 |
| Portugal | 11.70 | 6.37 | **-5.33** | -0.66 |
| Slovakia | 4.33 | 3.21 | **-1.12** | 3.03 |
| Slovenia | 7.71 | 10.67 | 2.96 | 8.50 |
| South Africa | 10.51 | 9.83 | **-0.68** | 4.10 |
| South Korea | 7.63 | 8.60 | 0.97 | 3.02 |
| Spain | 10.41 | 5.86 | **-4.55** | -0.32 |
| Sweden | 11.05 | 8.62 | **-2.43** | 0.20 |
| Switserland | 8.97 | 8.76 | **-0.21** | 1.05 |
| Turkey | 41.40 | 39.77 | **-1.63** | 14.05 |
| United Kingdom | 8.67 | 8.09 | **-0.58** | 0.57 |
| United States (NYSE) | 7.28 | 6.03 | **-1.25** | 0.09 |
| United States (NASDAQ) | 8.74 | 4.75 | **-3.99** | 1.42 |
| Developed markets | 9.2 | 7.30 | **-1.90** | 0.45 |
| Emerging markets | 13.08 | 13.94 | 0.86 | 6.2 |
| World market | 10.95 | 10.30 | **-0.65** | 3.05 |

*Notes: Results of the effect of the January dummy on the winter returns. Column one shows the mean returns for the winter periods in all the country. Column two lists the monthly mean winter returns controlled for the January dummy. Column three indicates the actual effect of the January dummy (calculated by subtracting the values of column one from column two). The bold numbers in column three represent the negative January effect. Column four shows the monthly mean summer returns for comparison. The adjusted January effect is defined as the excess returns achieved in January on top of the mean summer returns (Bouman, and Jakobsen, 2002).*

Since in 23 of the 31 countries the January returns are higher than the returns earned during the rest of the year we can establish that the January effect exists. This means that the January effect actually increases the seasonal gap in stock market returns in these countries. This finding contradicts both our initial expectations and the efficient market theory.

The next step is to look at the effect of data outliers on the strength of the Halloween effect. We expected the 1987 stock market crash as well as the 1998 Ruble crisis to be positively related to the Halloween effect. In order to test this hypothesis we compared the gap between the seasons before and after controlling for these data outliers.

In 26 of the 31 countries the t-values of the outlier dummy are significant at a 10% significance level (see table 3). In all countries, except for Slovakia, the t-values are negative. The information gathered so far is broadly sufficient to conclude that the October 1987 stock market crash and the August 1998 Ruble Crisis are negatively related to the performance of stock exchanges worldwide. This finding is hopeful for the critics of the “Sell in May, and go away” effect, since the highly significant t-values of the outlier dummy might explain why the summer returns are so much lower than the winter returns. But even though the outlier dummy is significant in 26 of the 31 countries, we still need to take a look at the effect of the outlier dummy on the monthly mean returns during summer. Since both outliers occur during the summer season the mean value of the summer returns of the 31 countries should generally move up after they are controlled for. So before discussing the rest of the results presented in table 3, let us take a look at the adjusted summer returns.

Table 3: Results after Controlling for The January Effect, T-Values of Adjusted Halloween Effect and the T-Value of The Outliers

| Country | T-value Halloween Effect controlled for the January Effect | T-value January Effect | T-value Halloween Effect Controlled for Outliers | T-value Outliers |
|---|---|---|---|---|
| Australia | 1.112 | -0.07 | 0.958 | -2.783*** |
| Austria | 2.332** | 0.424 | 2.3** | -3.94*** |
| Bangladesh | -1.463 | 0.136 | -1.572 | -1.116 |
| Belgium | 1.824* | 0.143 | 1.823* | -2.254** |
| Canada | 2.309** | 0.868 | 2.367** | -7.038*** |
| Chile | 0.471 | 0.774 | 0.427 | -5.144*** |
| China | 0.141 | 0.179 | 0.148 | -0.804 |
| Czech | 0.559 | 0.96 | 0.713 | -3.489*** |
| France | 2.608*** | -0.314 | 2.525** | -1.93* |
| Germany | 2.174** | 1.048 | 2.347** | -5.206*** |
| Hong Kong | -0.387 | 1.87* | -0.061 | -3.974*** |
| Hungary | 0.502 | 2.762*** | 1.159 | -3.654*** |
| India | 0.39 | -0.657 | 0.11 | -1.015 |
| Italy | 4.013*** | **-1.817*** | 3.392*** | -3.214*** |
| Japan | 2.068** | 2.335** | 2.73*** | -3.57*** |
| Malaysia | 1.672* | 0.44 | 1.027 | -6.172*** |
| Mexico | 0.993 | 0.473 | 1.19 | -3.799*** |
| Netherlands | 2.727*** | -0.49 | 2.392** | -5.126*** |
| Poland | 0.366 | 0.948 | 0.519 | -2.386** |
| Portugal | 1.145 | 2.27** | 1.737* | -2.404** |
| Slovakia | 0.226 | -0.617 | 0.053 | 0.145 |
| Slovenia | -0.885 | 2.816*** | -0.193 | -2.015** |
| South Africa | 0.231 | 1.928* | 0.473 | -5.331*** |
| South Korea | 0.696 | 0.838 | 0.977 | -0.218 |
| Spain | 1.373 | 1.516 | 1.536 | -5.26*** |
| Sweden | 1.83* | 0.881 | 1.878* | -4.48*** |
| Switserland | 1.841* | -0.538 | 1.547 | -4.155*** |
| Turkey | 1.1 | 1.826* | 1.576 | -2.502** |
| United Kingdom | 1.988** | 0.101 | 1.801* | -5.272*** |
| United States (NYSE) | 3.452*** | 0.221 | 3.347*** | -6.771*** |
| United States (NASDAQ) | 0.38 | 2.849*** | 0.908 | -4.021*** |

*Notes: The first column shows the t-values of the corrected Halloween effect. The second column shows the t-value of the January effect. Addition * means that the t-values are significant at a 10% significance level, ** at a 5% significance level and *** at a 1% significance level. The bold value for Italy refers to the fact that the January dummy is negatively related to the monthly mean returns. This negative relationship is significant at a 10% significance level. The third column shows the t-values of the adjusted Halloween effect. The fourth column shows the t-value of the outliers. The addition * means that the t-values are significant at a 10% significance level, ** at a 5% significance level and *** at a 1% significance level.*

Table 4 displays the summer returns after the adjustment of the outlier dummy was made. The third column shows the effect of controlling for the outliers on the monthly mean summer returns. It becomes clear that in 30 of the 31 countries the "outlier adjusted" summer mean returns are higher than the "non outlier adjusted" summer mean returns. Slovakia is the only country where the outliers actually have a positive effect on the summer returns. Furthermore, the outliers have a bigger effect on the summer returns in the emerging markets than on those in the developed markets (1.81% versus 1.12%).

It seems clear that controlling for the outliers decreases the gap between the winter and the summer returns. However, the central question is in how many countries the gap between winter and summer returns is significant. Before the outlier adjustments there were 16 countries where the winter returns were significantly higher than the summer returns on a 10% significance level (see table 1). When controlling for the outliers this picture changes. As table 3 shows, in 12 countries the winter returns are still significantly higher than the summer returns. We can conclude that the data outliers are indeed positively related to the Halloween effect; after controlling for the outliers the summer mean returns increase in all countries except for one. This means a decrease in the gap in returns between the seasons, which shows that the Halloween effect is in fact smaller than initially assumed; it has lost significance in four countries (see table 1 and 3).

Table 4: Effect of the Outlier Dummy on the Summer Returns

| Country | Mean Summer | Mean Summer Outlier Adjusted | Outlier Effect | Mean Winter |
|---|---|---|---|---|
| Australia | 2.93 | 3.83 | 0.90 | 7.06 |
| Austria | -2.13 | -0.33 | 1.80 | 12.27 |
| Bangladesh | 14.63 | 15.48 | 0.85 | -3.65 |
| Belgium | -0.83 | -0.21 | 0.62 | 8.33 |
| Canada | -0.16 | 0.43 * | 0.59 | 7.21 |
| Chile | 8.48 | 10.63 | 2.15 | 13.34 |
| China | 6.21 | 6.62 | 0.41 | 20.11 |
| Czech Rep. | 1.71 | 3.68 | 1.97 | 7.67 |
| France | -1.61 | -1.05 | 0.56 | 10.79 |
| Germany | -0.70 | 0.32 * | 1.02 | 7.84 |
| Hong Kong | 6.13 | 6.30 | 0.17 | 8.16 |
| Hungary | 4.19 | 6.85 | 2.66 | 15.40 |
| India | 8.42 | 8.84 | 0.42 | 10.91 |
| Italy | -3.78 | -2.41 | 1.37 | 13.29 |
| Japan | 0.86 | 1.34 | 0.48 | 8.00 |
| Malaysia | -1.98 | 0.89 * | 2.87 | 8.94 |
| Mexico | 7.13 | 12.53 | 5.40 | 22.81 |
| Netherlands | -0.68 | 1.10 * | 1.78 | 10.66 |
| Poland | 7.66 | 10.06 | 2.40 | 23.94 |
| Portugal | -0.66 | 0.39 * | 1.05 | 11.70 |
| Slovakia | 3.03 | 2.90 | **-0.13** | 4.33 |
| Slovenia | 8.50 | 9.48 | 0.98 | 7.71 |
| South Africa | 4.10 | 7.16 | 3.06 | 10.51 |
| South Korea | 3.02 | 3.06 | 0.04 | 7.63 |
| Spain | -0.32 | 2.26 * | 2.58 | 10.41 |
| Sweden | 0.20 | 2.29 | 2.09 | 11.05 |
| Switserland | 1.05 | 2.17 | 1.12 | 8.97 |
| Turkey | 14.05 | 7.07 | 3.02 | 41.40 |
| United Kingdom | 0.57 | 3.21 | 2.64 | 8.67 |
| United States (NYSE) | 0.09 | 0,84 | 0.75 | 7.28 |
| United States (NASDAQ) | 1.42 | 3.58 | 2.16 | 8.74 |
| Developed markets | 0.45 | 1.57 | 1.12 | 9.2 |
| Emerging markets | 6.2 | 8.01 | 1.81 | 13.08 |
| World market | 3.05 | 4.48 | 1.43 | 10.95 |

*Notes: Results of the effect of the outlier dummy on the summer returns. Column one shows the mean returns for the summer periods in all countries. Column two lists the mean monthly summer returns controlled for the outlier dummy. Column three indicates the actual effect of the outlier dummy (this is calculated by subtracting the values of column one from column two). Column four shows the monthly mean winter returns for comparison. The * in column two stands for countries which had negative monthly mean summer returns prior to the outlier adjustment and positive summer returns after the adjustment. The bold number in column three represents the only country where the outlier effect on the summer returns was negative. All numbers are given as percentages.*

Finally, we have to establish the combined impact of the January effect and the data outliers on the Halloween effect. From table 5 it becomes clear that the Halloween effect is significant in ten of the 31 countries at a 10% significance level. In two of these ten countries the season dummy is significant at a 1% level. As expected the combined effect of both control variables has again decreased the gap between the winter and summer returns. Before controlling for the January effect, the “Sell in May, and go away” effect was significant in 16 of the 31 countries at a 10% significance level (see table 1). After controlling for the outliers, this number dropped to 12 countries (see table 3). When controlling for the January effect 13 of the 31 countries showed a significant “Sell in May, and go away” effect at a 10% significance level (see table 3). So after controlling for both the outliers and the January effect, we can establish that the “Sell in May, and go away” effect is significant in ten countries. This means that the “Sell in May, and go away” effect loses its statistical significance after controlling for certain variables. It does occur, however, in almost one third of the countries with statistical significance (see table 5). Another important observation is that all of the ten countries with significant results for the season dummy in table 5 are developed countries. So after controlling for certain variables the "Sell in May, and go away" effect is no longer significant in any of the emerging markets (see table 1 and table 5).

Table 5: T-values of the Halloween Effect, the Outlier Effect and the January Dummy

| Country | T-value Halloween Effect Controlled for the Outlier Effect and the January Effect | T-value Outlier Effect | T-value January Effect |
|---|---|---|---|
| Australia | 0.932 | -2.775*** | -0.072 |
| Austria | 206** | -3.934*** | 0.436 |
| Bangladesh | -1.537 | -1.158 | 0.136 |
| Belgium | 1.691* | -2.249** | 0.144 |
| Canada | 1.982** | -7.037*** | 0.912 |
| Chile | 0.163 | -5.14*** | 0.819 |
| China | 0.087 | -0.802 | 0.179 |
| Czech | 0.386 | -3.489*** | 0.99 |
| France | 2.499** | -1.93* | -0.316 |
| Germany | 1.915* | -5.206*** | 1.074 |
| Hong Kong | -0.629 | -3.984*** | 1.897* |
| Hungary | 0.268 | -3.719*** | 2.848*** |
| India | 0.302 | -1.014 | -0.657 |
| Italy | 3.805*** | -3.228*** | **-1.848*** |
| Japan | 1.898* | -3.582*** | 2.335** |
| Malaysia | 0.801 | -6.163*** | 0.459 |
| Mexico | 0.913 | -3.815*** | 0.416 |
| Netherlands | 2.432** | -5.119*** | -0.511 |
| Poland | 0.206 | -2.368** | 0.959 |
| Portugal | 0.985 | -2.433** | 2.302** |
| Slovakia | 0.236 | 0.145 | -0.615 |
| Slovenia | -1.043 | -2.058** | 2.844*** |
| South Africa | -0.178 | -5.396*** | 2.111** |
| South Korea | 0.679 | -0.218 | 0.837 |
| Spain | 0.99 | -5.277*** | 1.596 |
| Sweden | 1.516 | -4.478*** | 0.913 |
| Switserland | 1.64 | -4.148*** | -0.557 |
| Turkey | 0.955 | -2.514** | 1.847* |
| United Kingdom | 1.682* | -5.264*** | 0.105 |
| United States (NYSE) | 3.145*** | -6.766*** | 0.075 |
| United States (NASDAQ) | -0.023 | -4.074*** | 2.978*** |

*Notes: The first column shows the t-values of the Halloween effect controlled for the Outlier effect and the January effect. The second column lists the t-values of the Outlier effect. The third column shows the t-values of the January dummy. Addition * means that the t-values are significant at a 10% significance level, ** at a 5% significance level and *** at a 1% significance level. The bold value for Italy means that the January dummy is negatively related to the monthly mean returns. This negative relationship is significant at a 10% significance level.*

Next, we have to address the following questions: What is the effect of the type of market on the "Sell in May, and go away" effect and is there a significant difference between the emerging and the developed markets with respect to winter and summer returns? In order to address the stated questions we conducted another regression analysis.

Table 6: Significant Level

| t-value "market type" dummy | t-value Halloween Effect |
|---|---|
| -1.545 | 6.497 * |

*Notes: The first column shows the t-value of the "market type" dummy. The second column gives the t-value of the first dummy variable $S_t$. The values with an extra added * are significant at a 1% significance level.*

The first outcome of the regression analyses is the t-value (-1.545) of the market dummy. This value does not seem to be statistically significant at a 10% significance level (see table 6). So the first thing we can conclude is that the relationship between monthly mean returns and the type of market (developed versus emerging) is not significant. The relationship is in fact negative; in this case it means that monthly mean returns are more negatively related to developed markets than to emerging markets. This information basically tells us that the overall mean returns are lower in developed markets than in emerging markets. Table 4 confirms this.

The second outcome of the regression analysis shows the relationship between the season dummy and the dependent variable. It seems that this relationship is significant (1 % significance level) and positive (6.497*). Monthly mean returns are positively related to the winter season for both types of markets. The central question again is, of course, whether the seasonal differences between the market types are significant.
Table 6 shows the average winter and summer returns in both types of markets. It becomes clear that the average returns of both seasons are higher in the emerging markets. Again however, although the gap between the seasons is bigger in the developed markets the crucial question is whether this difference is significant. It appears that the type of market plays a significant role in the discrepancy in the seasonal returns. This difference is rather large; it has a 5% significance level (see table 7).

Table 7: Significant Level

| f-value "difference in the Halloween effect between different market types" | Significance |
|---|---|
| 4.267 ** | 0.039 |

*Notes: Table 7 shows the significance of the difference in season returns between the developed and emerging markets. Column 1 shows the f-statistic while column 2 shows the significance. * Sign means that the f-value is significant at a 5% significance level.*

So with respect to the second question we can conclude that the difference in the seasonal returns between developed and emerging markets is significant. Emerging markets are characterized by higher average returns over the year. These higher returns are mainly caused by the higher summer returns compared to those of the developed markets. The higher summer returns in emerging markets lead to a lower gap in seasonal returns. As our previous results show, the "Sell in May, and go away" effect is the strongest and most prominent in the developed markets. This finding is in line with our expectations.

Our third topic of discussion pertains to the Halloween effect at industry level. To investigate this issue we used a sample of in total three countries of which six industries were studied per country. The countries were the Netherlands, Sweden, and the United Kingdom. The sectors observed were consumer goods, consumer services, energy, financials, industrials, and beverages/food.

We can see that in 15 of the 18 sectors the winter returns are higher than the summer returns (the probability calculation is approximately 0.3% assuming efficient market theory). The probability was calculated as follows: 0.5^18*(NcR 18-3). The Netherlands shows the smallest number of sectors where the winter returns are higher than the summer returns, namely four. Sweden is second with five out of six sectors. In the United Kingdom all sectors have higher winter than summer returns. This pattern may be related to the length of the time frame during which the countries were studied. It seems that the longer this timeframe, the larger the number of industries which exhibit higher winter than summer returns. Again the central question is whether the season effects are significant, and if so, at what level. In 6 of the 18 industries the winter returns are significantly higher than the summer returns. What is striking to see is that in the Netherlands none of the six sectors exhibit significant differences in season returns. In Sweden and the UK half of the sectors show significant differences between the seasons. The reason for the lack of significant differences in the Netherlands (see table 7) appears not to be caused by high summer returns but by the low returns obtained during the winter period. This may simply be explained by the smaller amount of data, obscuring the actual situation in the Netherlands. In this respect we refer to the general index for the Netherlands, which shows significant differences between the seasons even after controlling for the outlier dummy and the January dummy (see table 5)

Table 8: Halloween Effect at Sector Level and Significance of the "Sell In May, and Go Away" at Sector Level

| Country | Sector | Number of Observations | Winter Returns | Summer Returns | T-Value "Sell In May" |
|---|---|---|---|---|---|
| Netherlands | Consumer services | 72 | **5.595** | 0.867 | 1.434 |
| | Consumer goods | 72 | **6.494** | -0.659 | 0.507 |
| | Energy | 72 | -0.199 | 0.874 | -0.22 |
| | Financials | 72 | **5.815** | -3.301 | 0.396 |
| | Industrials | 72 | **10.71** | -7.519 | 0.137 |
| | Beverages/food | 72 | -7.786 | -5.267 | 0.283 |
| Sweden | Consumer services | 144 | **23.727** | 6.2 | 1.568 |
| | Consumer goods | 144 | **14.878** | 3.295 | 1.531 |
| | Energy | 144 | 7.515 | 14.078 | -0.71 |
| | Financials | 144 | **16.53** | -1.552 | **2.348**** |
| | Industrials | 144 | **16.773** | -3.096 | **2.844***** |
| | Beverages/food | 144 | **12.621** | 1.602 | **2.099**** |
| United Kingdom | Consumer services | 156 | **8.746** | -4.429 | **2.29**** |
| | Consumer goods | 156 | **5.803** | -1.086 | 0.865 |
| | Energy | 156 | **8.251** | 2.497 | 0.911 |
| | Financials | 156 | **7.841** | 1.413 | 0.514 |
| | Industrials | 156 | **8.556** | -5.81 | **1.731*** |
| | Beverages/food | 156 | **10.365** | -2.24 | **1.891*** |

*Notes: Table 7 summarizes the results of the industry analysis for the three countries. Column 1 lists all the industries. Column 2 shows the number of monthly means observed per country per industry. Column 3 and column 4 indicate the winter and the summer returns per industry per country. The bold values in column 3 represent the industries where the winter returns are higher than the summer returns. The fifth column shows the t-value of the "Sell in May" effect. The sign * means that the t-values are significant at a 10% significance level, ** at a 5% significance level and *** at a 1% significance level.*

In conclusion we can establish that there is some overlap in seasonal differences among the different sectors. Sweden and the United Kingdom can be better compared because the timeframes during which they were studied are almost the same. Here the results for the beverages/food and industrials sectors are identical. We can also see that the energy sector does not appear to be suitable for the "Sell in May, and go away" investment strategy.

Finally, the most important question we have to answer is whether investors can actually benefit from the "Sell in May, and go away" investment strategy. If the returns obtained during the summer period are higher than the interest rate offered on treasury bills minus the transaction costs, the buy-and-hold-strategy will prove more profitable (see table 9).

Buy-and-hold "wins", if:

$$r_{summer} > i_{T\text{-}bill} - TC \tag{4}$$

where $r_{summer}$ stands for returns during summer, $i_{T\text{-}bill}$ stands for interest rate on t-bills, and TC stands for transaction costs.

Table 9: Sell in May versus Buy-and-hold

| Country | Observation Period | Halloween Mean | Halloween Standard Deviation | Buy-and-Hold Mean | Buy-and-Hold Standard Deviation |
|---|---|---|---|---|---|
| Australia | 1993-2006 | 13.55 | 4.98 | 9.708 | 7.93 |
| Austria | 1986-2006 | 21.48 | 12.02 | 9.63 | 19.01 |
| Belgium | 1990-2006 | 14.69 | 7.9 | 7.73 | 12.45 |
| Canada | 1969-2006 | 15.99 | 8.57 | 6.79 | 11.90 |
| Chile | 1993-2006 | 16.81 | 11.15 | 15.4 | 16.65 |
| Czech Rep. | 2001-2006 | -2.82* | 9.73 | 0 | 14.14 |
| France | 1988-2006 | 17.52 | 9.16 | 9.14 | 14.91 |
| Germany | 1965-2006 | 15.10 | 9.79 | 6.86 | 15.17 |
| Italy | 1992-2006 | 23.54 | 12.32 | 10.16 | 18.00 |
| Japan | 1989-2006 | 4.43 | 11 | -2.09 | 15.53 |
| Netherlands | 1983-2006 | 17.30 | 9.34 | 9.73 | 14.44 |
| Poland | 2001-2006 | 22.60* | 10.8 | 25.55 | 17.15 |
| Portugal | 1994-2006 | 18.18 | 15.39 | 7.74 | 19.84 |
| Slovakia | 2001-2006 | 19.10* | 24.2 | 27.65 | 26.73 |
| Slovenia | 2003-2006 | 18.32* | 16.08 | 27.83 | 16.97 |
| South Africa | 1996-2006 | 23.50 | 10.34 | 14.52 | 16.06 |
| South Korea | 2001-2006 | 21.13 | 15.13 | 17.79 | 21.27 |
| Spain | 1987-2006 | 19.21 | 11.69 | 9.53 | 15.90 |
| Sweden | 1987-2006 | 20.33 | 12.56 | 11.88 | 18.06 |
| Switserland | 1989-2006 | 13.20 | 8.79 | 10.45 | 13.20 |
| United Kingdom | 1979-2006 | 17.82 | 6.64 | 9.25 | 10.30 |
| United States (NYSE) | 1955-2006 | 14.09 | 7.44 | 6.81 | 10.35 |
| United States (NASDAQ) | 1983-2006 | 16.13 | 19.35 | 9.89 | 23.04 |
| **Average total** | | **16.57** | **11.49** | **11.39** | **16.04** |

*Notes: Table 9 shows the results concerning the profitability of the "Sell in May, and go away" strategy and the buy-and-hold strategy. The third column shows the yearly mean returns for the Halloween "Sell in May", and the fourth column indicates the standard deviation. The fifth column represents the yearly mean for the buy-and-hold strategy. The last column shows the standard deviation for the buy-and-hold strategy. Addition * means that the yearly returns obtained by following the Halloween strategy were lower than the yearly returns obtained by following the buy-and-hold strategy.*

The interest rates were taken from the data stream per country investigated. The transaction costs, on the other hand, were equalized across all countries and fixed at a rate of 0.1% per single transaction. This number was based on the information provided by the website of ABN AMRO. In addition, the transaction costs were estimated to be 0.1% on future markets (Solnik, 1993).

Table 9 shows the results obtained for the 23 markets investigated. It seems that the "Sell in May" strategy outperforms the buy-and-hold strategy in 19 of the 23 markets. Interestingly, the four markets where the buy-and-hold strategy outperforms the "Sell in May" strategy are all located in Central-Eastern Europe. These countries are the Czech Republic, Slovakia, Poland and Slovenia. This can firstly be explained by the limited time spans during which these four countries were studied. Slovenia was observed for only four years, while the other countries were examined for six years. Short timeframes increase the impact of outliers, thereby undermining the reliability of the entire picture.

Table 10: Summer Returns Comparing the Czech Republic, Poland, Slovakia and Slovenia

| Country | Observation Period | Average Summer Returns | Observation Period | Average Summer Returns |
|---|---|---|---|---|
| Czech Rep. | 1995-2007 | 1.71 | 2001-2006 | 7.2 |
| Poland | 1992-2007 | 7.66 | 2001-2006 | 9.21 |
| Slovakia | 1995-2007 | 3.03 | 2001-2006 | 12.86 |
| Slovenia | 1994-2007 | 8.5 | 2003-2006 | 7.87 |

*Notes: Table 10 compares the summer returns in the different periods for the four countries.*

Furthermore, as indicated, three countries show higher summer returns during the sample period than their average summer returns (see table 10). Especially in the Czech Republic and Slovakia this difference is remarkable. This is not the case in Slovenia where the average summer returns are higher than the summer returns during the four year sample period. However, we should remember that in Slovenia this is generally the case (see figure 2). So here there is no evidence of the Halloween effect. Another point worth mentioning is that the Czech Republic and Poland show no significant difference between their winter returns and their summer returns (see table 1); in these countries the winter returns are higher than the summer returns. Given the overall high summer returns in Slovenia as well as in the other three countries during the observation period, "buy-and-hold" is a more profitable strategy for these countries than "Sell in May, and go away".

When looking at the average score of the 23 markets we can conclude that the Halloween strategy is definitely the ultimate winner with an average annual mean of 16.57% versus the 11.39% of the buy-and-hold strategy. Further, in addition to the higher returns, the Halloween strategy's standard deviation level is more than 4.5% lower than that of buy-and-hold (see table 9). The "Sell in May, and go away" strategy appears to outperform the simple buy-and-hold approach on two fronts by offering higher annual returns combined with a lower standard deviation. When comparing the two it becomes clear that the Halloween strategy is less risky and generates more money than the buy-and-hold strategy. This finding is not in line with our initial expectations.

## DISCUSSION

In this section we will present some arguments for the existence of the Halloween effect. Our first argument refers to its economic significance. An irregularity can only exist if it is economically significant. In turn, economic significance depends on economic benefits and costs. Costs include, among many things, transaction costs, which are often not accounted for when analysing an irregularity. As a result, irregularities often only exist in theory. In our analysis, however, we did include transaction costs, and because the "Sell in May, and go away" investment strategy still proved superior we can reject transaction costs as one of the explanations for the Halloween effect.

Our second argument for the existence of the Halloween effect or of any other anomaly for that matter, is data mining. Data mining is the process of retrieving knowledge from data-bases stored in data marts or data warehouses (Cooper and Schindler, 2001). However, data mining can be problematic, especially when researchers do not report the number of unsuccessful mining attempts before presenting a particular pattern (McQueen, Grant and Thorley, 1999). In this way they do not show the full picture of their research. "Too much digging" is a well-known pitfall of data mining (Leinweber, 1998). This, however, does not apply to the Halloween effect since its existence has been recognised for over a long period of time and in most of the countries studied. The second pitfall of data mining is the lack of theory. In the case of the Halloween effect there is no formal theory; it is merely based on an old market saying which goes: "Sell in May, and go away". This saying was known long before any empirical tests were ever performed in this area. This means that the Halloween effect is not a 'product' of empirical findings. Hence this phenomenon is not associated with the data mining fallacy.

The third argument for the Halloween effect concerns the concept of risk. It makes perfect sense to question whether the level of risk throughout the year is actually sufficiently in balance with the expected returns according to the Halloween effect. The Capital Asset Pricing Model (CAPM) states that the expected rates of return as demanded by the investors depend essentially on two factors. First of all, on the time value of money, and second on the risk premium (Brealey, Myers and Marcus, 2004). Ghysels, Santa-Clara, and Valkanov (2005) have investigated the trade-off between the variance of stock market return and its mean. They observe a positive and significant relationship between risk and return. Since the winter returns are higher than the summer returns, we would expect to find a higher rate of risk during the winter. This, however, does not seem to be the case (see table 4). We can thus reject risk as one of the explanations for the Halloween effect.

A fourth factor proving the existence of the Halloween effect could be the January effect. As we can read from table 3, controlling for the January effect decreases the strength of the Halloween effect. We can therefore argue that the January effect is indeed related to the Halloween effect, although it can only partially explain the latter's existence.

The data outliers used are the fifth possible explanation for the Halloween effect. Table 5 tells us that in most countries the Halloween effect weakened once the data outliers were controlled for. Therefore we can conclude that these data outliers also partially explain the existence of the Halloween effect.

The sixth argument for the Halloween Effect is the vacation period. This can be explained as follows. Investment activities are associated with risk. During the vacation time the number of investors temporarily decreases, which means that the group dealing with risk becomes smaller. This smaller group demands higher risk premiums, which in turn leads to a decrease in prices during the vacation shift. This price decrease occurs automatically because the market offers the investors higher returns.

Seasonal Affective Disorder (SAD) is the seventh factor in the explanation of the Halloween effect. SAD, also known as winter depression, is a mood disorder which manifests itself every winter. People suffering from SAD experience serious mood changes during this time. The psychological cause of SAD is associated with a lack of daylight. A common treatment for SAD is light therapy. Avery (Avery et. al., 2001) has tested the influence of light therapy by using the Hamilton Depression Rating.

Their study shows that the larger the number of hours of sunshine during a week, the more positive the patients responded. Low returns are generally expected during the winter period. Once the days are getting longer again, SAD decreases and people regain their confidence in taking risks. The fact that the portfolios of investors become riskier during this period is an illustration of this pattern. And as soon as portfolios become riskier, the expected returns increase as a result of the higher risk a premium, which in turn leads to an increase in the stock returns. SAD has a significant effect on stock market returns, especially in countries located at higher latitudes (Kamstra et. al., 2003). What is important to mention, however, is that Kramer et. al., have not taken the total hours of daylight and sunshine into account. What happens if autumn is extremely sunny and the number of hours of sunlight is higher than average? Does this affect the expected outcome? These issues have not been discussed yet, making SAD a rather weak factor in the explanation of the Halloween effect. Moreover, no real differences have been found among countries at different latitudes.

The eighth factor is the optimism cycle. The optimism cycle is based on the idea that people, financial forecasters, and investors in particular, are in general excessively optimistic (Doeswijk, 2005). According to this theory there is a seasonal cycle in how investors feel about the market and perceive the future. As the end of the year approaches investors start looking forward to the next year by displaying levels of optimism about possible future earnings which are basically too high. Chung and Kryzanowski (2000) show that also forecasters of the S&P 500 index tend to be too optimistic about the possible earnings in the next year. It is mainly this "over optimism" which creates a seasonal pattern in the industry returns. As a result of this excessive optimism in the beginning of the year the stock returns increase; investors are willing to take more risk and so they invest more. However, the level of optimism starts to decrease once reality presents itself. This happens usually after the first quarter results have been made public. During this time the investors realise that their view was too optimistic, and from that moment on their pessimism about the future increases. The optimism cycle theory recommends investors to overweigh equities during the "positive" period and underweigh them during the "pessimistic" period. The positive period spans from the last couple of months of the year until the first months of the next year, which is almost similar to the winter period of the Halloween effect.

The weather could be regarded as yet another factor which influences the seasonality in the stock market returns. Saunders (1993) studies the effect of the weather in New York City on the index changes of NYC stock-listed companies. Weather creates and shapes the environment, which in turn affects people's moods. Mood changes can influence the willingness of investors to take risks. In this way, the weather can affect investing behaviour. Saunders (1993) argues that sunny days increase investors' optimism, resulting in higher market returns. Cloudy days, on the other hand, make investors more pessimistic and less willing to take risks, leading to lower market returns. Saunders also verifies that the difference in stock market returns between the sunniest and the cloudiest days is statistically significant. Cao and Wei (2005) examine the relationship between temperature and stock market returns. Together with length of day and number of hours of sunshine, temperature is considered as the most influential weather variable. In their paper Schneider et al. (1980) conclude that high temperature is mostly associated with predominant feelings of indifference and lethargy, whereas cold temperatures mainly coincide with feelings of aggression. It is this aggression which affects investors in terms of their mood and risk perception, making them more risk-oriented. High levels of temperature are thus linked with lower levels of risk taking. The inverse relationship between temperature and stock market returns is a possible explanation for this seasonal cycle.

## CONCLUSION

This research has provided evidence for the existence of the Halloween effect. Significant differences were found between the winter and summer returns in most countries examined. We also established that in most countries both the January effect and the data outliers have a moderating effect on this gap between the seasonal returns.

Further, we observed a significant difference in the strength of the Halloween effect between mature and emerging markets in terms of their seasonal returns. We have come to the conclusion that the Halloween effect is stronger in the developed markets than in the emerging markets. With respect to our industry-level analysis, in which we investigated six industries in three different countries, we can conclude that in 15 of these 18 industries the winter returns were higher than the summer returns (see table 7). In addition, in two of the three countries the energy sector showed higher summer than winter returns.

Finally, we compared the profitability of the "Sell in May, and go away" investment strategy with that of the buy-and-hold strategy. It appeared that in 19 of the 23 countries studied the "Sell in May" strategy proved to be more profitable. The four countries to which this finding did not apply were all located in Central-Eastern Europe. It has to be added however that their observation period was rather short. During the observation period their summer returns were higher than the average summer returns, which made the buy-and-hold strategy more profitable for these countries.

It must be noted, however, that neither the outliers nor the January effect was taken into account in our calculation. In order to create a realistic picture we did not control for these variables. Because in real life one cannot perfectly control for the effect of data outliers neither did we control for it. So by not including them we tried to mimic real life. Obviously, if we had controlled for the outliers and the January effect, the profitability of the Halloween strategy would have decreased.

A limitation of this research pertains to the difficulty to apply the “Sell in May, and go away” investment strategy to best advantage in real life. This is because of the value-weighted index used in our calculations for each country. The value-weighted index changes the mean values and involves huge transaction costs. However, the “Sell in May, and go away” principle still allows investors to adjust their market portfolio each year when they sell their safe assets. Using a value-weighted index was the most accurate way of imitating reality.

In order to find out more about the Halloween effect more countries still need to be investigated. This is necessary to expand our knowledge of the impact of the Halloween effect on a global level. Examining more countries would also contribute to increasing our understanding of the differences between developed and emerging markets. In addition, more research should be conducted on the industry-level to trace the origins of the Halloween phenomenon. Bouman and Jakobsen (2002) mention that the Halloween effect goes back as far as the UK stock market in the late 17$^{th}$ century. However, if one argues that investors are not aware of the opportunity offered by the Halloween effect, one implies that it could disappear if one really wanted it to. If everybody were to invest in risk-free assets during the summer, all parties would benefit. If this actually happened, the interest rates earned by the risk-free assets would decrease, thereby lowering the summer pay-off of the “Sell in May, and go away” investment strategy. This means that there is a point at which the Halloween and the buy-and-hold payoffs are equalized, depending among other factors on how many investors choose to follow the Halloween strategy.

This line of reasoning could be one of the many solutions to the Halloween puzzle, namely the percentage of investors who invest according to the Halloween strategy. In other words, the larger the number of investors adopting the Halloween strategy, the less these investors will benefit from it. This circumstance then automatically leads to a decrease in the number of people using the Halloween strategy, which again diminishes its impact and thereby its rationale.

On the other hand, the Halloween effect could be a phenomenon which is embedded in the entire spectrum of external factors which influences people’s behaviour. Perhaps the priorities of investors differ depending on the seasons; earning maximum profits may have less priority during the summer than during the winter.

It is clear that the Halloween effect cannot be explained by one factor, but that it is influenced by many different aspects in many different fields. And although the true reason for its existence is hard to pinpoint, we know that it is out there and that it pays off to pursue this strategy. So while continuing our investigation into the true causes of the Halloween effect, let us go about our business in our usual manner and simply enjoy the profits it generates.

## REFERENCES

Avery, D., D. Eder, M. Bolte, C. Hellekson, D. Dunner, M. Vitiello and P. Prinz, (2001), ‘Dawn simulation and bright light in the treatment of SAD: a controlled study’, *Biological Psychiatry* 50 (3), 205-216.

Bouman, S. and B. Jakobsen, (2002), 'The Halloween Indicator, "Sell in May, and go away": Another Puzzle', *The American Economic Review*, Vol. 92, No. 5, 1618-1635.

Brealey, R., S. Myers and A. Marcus, (2004), 'Fundamentals of Corporate Finance', McGraw-hill, International Edition 2004.

Cao, M. and J. Wei, (2004), 'Stock Market Returns: A Temperature Anomaly', *Journal of Banking and Finance,* forthcoming.

Chung, R. and L. Kryzanowski, (2000), 'Market Timing Using Strategists' and Analysts' Forecasts of S&P 500 Earnings per Share', *Financial Services Review*, Vol. 9, No. 2, 125-144.

Cooper, D. and P. Schindler, (2001), 'Business Research Methods', McGraw-Hill, International Edition 2001.

Doeswijk, R,. (2005), 'The Optimism Cycle: Sell in May', IRIS (Rabobank/Robeco), Working paper.

Ferguson, M. F. and H.D. Witte, Congress and the Stock Market (March 13, 2006). Available at SSRN: http://ssrn.com/abstract=687211.

Ghysels, E., P. Santa-Clara and R. Valkanov, (2005), 'There is a risk-return trade-off after all', *Journal of Financial Economics*, 76, 509-548.

Haug, M. and M. Hirschey, (2006), 'The January Effect', *Financial Analysts Journal*, Vol. 62, No. 5, CFA Institute

Hirshleifer, D. and T. Shumway, (2003), 'Good day sunshine: Stock returns and the weather', *The Journal of Finance* 58, 1009-1032.

Henry B. and J. Nixon, (1998), 'The Crisis in Russia: Some Initial Observations', *Economic Outlook*, Vol. 23, No. 1.

Kamstra, M., L. Kramer and M. Levi, (2003), 'Winter Blues: A SAD Stock Market Cycle', *American Economic Review*, 93 (1), 324-343.

Leinweber, D., (1998), 'Stupid Data Miner Tricks: Overfitting the S&P 500', Annotated slide excerpts. First Quadrant Corporation.

Maberly, E. D and R. M Pierce, (2004), 'Stock Market Efficiency Withstands another Challenge: Solving the "Sell in May/Buy after Halloween" Puzzle', *Economic Journal Watch*, Atlas Economic Research Foundation, Vol. 1(1), April, 29-46.

McQueen, R. Grant and S. Thorley, (1999), 'Mining Fool's Gold', *Financial Analyst Journal*, 55 (2), 61-72.

Santa-Clara, P. and R. Valkanov, (2003), 'The Presidential Puzzle: Political Cycles and the Stock Market', *The Journal of Finance*, 43, 1841-1872.

Saunders, E., (1993), 'Stock Prices and Wall Street Weather', *American Economic Review,* Vol. 83, No. 5, 1337-1345.

De Santis, Giorgio and S. Imrohoroglu, (1997), 'Stock returns and volatility in emerging financial markets,' *Journal of International Money and Finance,* Elsevier, vol. 16(4), pages 561-579, August.

Schneider, F., W. Lesko and W. Garrett, (1980), 'Helping behaviour in hot, comfortable and cold temperature: A field study', *Environment and Behaviour*, 2, 231-240.

Solnik, B., (1993), 'The Performance of International Asset Allocation Strategies Using Conditioning Information', *Journal of Empirical Finance,* 1 (1), 33-55.

Website of ABN AMRO Bank: http://www.abnamro.nl/nl/beleggen/tarieven/overzicht.html

## BIOGRAPHY

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