The Halloween Indicator, "Sell in May and Go Away": Another Puzzle

By Sven Bouman and Ben Jacobsen*

> The Stock Exchange world is in a sort of twilight state at the moment. The potential buyers seem to have "sold in May and gone away" ... .
>
> *Financial Times,* May 30, 1964, p. 2

Every year, usually in the month May, the European financial press refers to a—presumably—old and inherited market saying: "Sell in May and go away."[1] According to this saying, the month of May signals the start of a bear market, so that investors are better off selling their stocks and holding cash. There are two different endings to the saying. The first of these is: "but remember to come back in September"; the second is: "but buy back on St. Leger Day"—in which "St. Leger Day" refers to the date of a classic horse race run at Doncaster in England every September. According to the saying, stock returns should be lower during May through September than during the rest of the year, and although many Americans tend to be unfamiliar with it, Michael O'Higgins and John Downes (1990) report a closely related and similar strategy related to market timing. Referred to as the Halloween indicator, it is "so named because it would have you in the stock market starting October 31 and through April 30 and out of the market for the other half of the year."

This paper examines whether stock returns are indeed significantly lower during the May–October period than during the remainder of the year. While we report results for the month October, results are similar when we use September instead. Surprisingly, we find the Sell in May effect is present in 36 of the 37 countries in our sample. The effect tends to be particularly strong and highly significant in European countries, and also proves to be robust over time. Sample evidence shows that in a number of countries it has been noticeable for a very long time, and in the U.K. stock market, for instance, we have found evidence of a Sell in May effect as far back as 1694. We find no evidence that the effect can be explained by factors like risk, cross correlation between markets, or the January effect. We also try some

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[1] Some illustrative quotes: "There's an old axiom about the market: Sell in May and go away" (*Forbes*, 1996, p. 310). "With all that to wait for, rarely has the old stock market adage to 'sell in May and go away' been more apposite" (*The Economist*, 1993, p. 26). " 'SELL in May and go away,' says the old adage" (*The Economist*, 1992, p. 71). " 'Sell in May and go away' is one of the best known and most often cited market wisdoms, and many generations of traders grew up hearing this wisdom" (translated from German, www.bank.de/infos/presse/technical-market-view.htm).

alternative explanations—that we discuss later in this paper—but none of them seems to provide an explanation for the puzzle.

The Sell in May effect is an interesting puzzle for several reasons.

Firstly, we find that it is—unlike other calendar effects—not only present in most developed markets, but also in emerging markets. For instance, Stijn Claessens et al. (1995) find no evidence that several well-known calendar anomalies exist in a sample of 20 emerging stock markets. In particular they find no evidence of a January effect.

Secondly, the anomaly does not suffer from Murphy's law as documented by Elroy Dimson and Paul Marsh (1999). This means that unlike many other anomalies, this anomaly does not—at least not yet—seem to disappear or reverse itself after discovery, but continues to exist even though investors may have become aware of it. While we do not know exactly how old the saying is,[2] we have a written reference to the Sell in May effect in an issue of the *Financial Times* from 1964. Moreover, in the popular press the saying has been cited frequently over the years. A search in Lexis-Nexis, for example, results in some 150 references in English over the past 25 years, while the oldest reference in a computer-searchable news source (Lexis-Nexis) is from May 7, 1977, p. 109 in *The Economist* ("But if the market falters some institutions will be strongly tempted to take their profits and give the market a rest during summer—traditionally a time when equities perform unexcitingly. Sell in May and go away?"). The market saying is frequently cited in the popular press; however, academic literature has paid it no more than lip service, Mario Levis (1985) being the only academic source to mention it at all. Most of the stock market time series we use here begin after 1964 [most developed market series start at the end of 1969 and several shorter series (including emerging markets) in 1988], and this suggests that investors could have been well aware of the existence of the saying at the start of that period. Thus, the main data series we use can be seen as out-of-sample returns.

Thirdly, the economic significance of this particular calendar anomaly is considerable. A simple trading strategy based on the saying would outperform a buy and hold portfolio in many countries in our study, and would also be a lot less risky.[3] This also makes the Sell in May effect potentially interesting for practitioners, as benefits can be obtained by just two trades a year and are therefore not wiped out by transaction costs.

Fourthly, data snooping as suggested by Ryan Sullivan et al. (2001) seems an unlikely explanation for the Sell in May anomaly. In their paper they find that the discovery of well-known calendar effects such as the January effect or the Monday effect might, in fact, be spurious and a purely data-driven result. These particular calendar rules are selected from a large universe of calendar rules, and using a bootstrap procedure that explicitly measures the distortions induced by data snooping, the paper's authors find no evidence of significant calendar effects in the United States. The difference in the case of the Sell in May effect is that the data-snooping argument does not apply. The effect is not just another calendar rule taken from the range of calendar rules, but an effect that is based on an inherited market saying (and the number of rules induced by market sayings seems limited).

Last but certainly not least, our results also seem to pose another surprising puzzle and a challenge to accepted financial theory: why are (excess) returns not significantly different from zero, or often negative, during the summer months?

Many seasonal effects have of course already been reported in literature. Some well-known anomalies are the Monday effect, the Friday effect, the Turn of the Month effect, the Holiday effect and the January effect. However, due to transaction costs it is generally difficult to exploit these anomalies and actually make a profit.[4] Gabriel Hawawini and Donald B. Keim (1995)

[2] *Collins Dictionary of Business Quotations* describes it as an "anonymous stock market maxim."

[3] We consider the economic significance of a trading strategy in detail in the Appendix.

[4] Although an investor can implicitly profit from these anomalies by postponing or push forward buying (selling)

provide an overview of research in this area and Anup Agrawal and Kishore Tandon (1994) report extensive international evidence on many seasonal effects. Claessens et al. (1995) investigate whether these anomalies are also present in emerging markets.

The Sell in May effect or the Halloween effect has to our knowledge not been (thoroughly) investigated before. Levis (1985) refers to the Sell in May effect but does not examine whether or not it actually exists. O'Higgins and Downes (1990) provide some results, but do so only for the United States market. In addition, they fail to analyze the statistical significance of their findings.

This paper is organized as follows. In Section I we present the puzzle and discuss the data and the methodology we have used. Section II contains a short discussion of possible explanations and of the tests performed. Section III contains our conclusions.

I. The Puzzle

Assuming market efficiency, one would be doubtful as to whether or not there could be any truth in a simple and inherited market saying such as "Sell in May and go away." Clearly—apart from possibly a January effect—there are no reasons to assume that market returns in the period of May to October would be significantly different from the remainder of the year. Or, to put it another way, the chance of finding a Sell in May effect is 50 percent or 0.5, and assuming market efficiency and independent stock markets around the world, the chance of finding a Sell in May effect in every country out of 37 countries would equal 0.5^{37} or 0.73×10^{-12}. But despite the fact that from a theoretical point of view the presence of a Sell in May effect seems implausible, the popular press (mostly in the month of May) continues to refer to it year in, year out. In 1999 and 2001, the Sell in May effect was even discussed on CNN. The main focus in the media is whether or not the old market saying will hold up during the summer period to come. In addition, while almost every journalist refers to the saying as being old, nobody knows exactly how old it is. Here we test whether there is some truth at all to Sell in May.

A. *Data*

For our investigation we start with (continuously compounded) the monthly stock returns of the value-weighted market indices[5] of 19 countries (local currencies). These countries are: Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Ireland, Italy, Japan, The Netherlands, Norway, Singapore, South Africa, Spain, Switzerland, the United Kingdom, and the United States. All series are MSCI reinvestment[6] indices (local currency) over January 1970–August 1998, except the index for South Africa which starts in 1973 and is taken from Datastream. We also use data from markets for which MSCI reinvestment indices are available since 1988. Among these series are several emerging markets series. Claessens et al. (1995) argue that due to their higher degree of segmentation they provide an interesting "out-of-sample" test. Whether or not emerging markets are (partially) segmented or integrated is still an ongoing discussion.[7] Many of these so-called emerging markets are, in fact, fully "integrated" in the sense that there are no restrictions on capital mobility. We consider these series as a first "out-of-sample test" for the

when he or she has already decided to purchase (sell) certain stocks.

[5] One advantage of the value-weighted indices is that these indices exhibit less autocorrelation and are less influenced by the January effect, since the January anomaly is closely related to the small-firm effect (see, for instance, Hawawini and Keim, 1995).

[6] In the developed markets, MSCI calculates dividend reinvestment at the end of each month as 1/12th the indicated annual dividend. There are no lags instituted for the reinvestment of the dividend. MSCI has constructed its Emerging Markets dividends reinvested series as follows: In the period between the ex-date and the date of dividend reinvestment, a dividend receivable is a component of the index return. Dividends are deemed received on the payment date. To determine the payment date, a fixed time lag is assumed to exist between the ex-date and the payment date. This time lag varies by country, and is determined in accordance with general practice within that market. Reinvestment of dividends occurs at the end of the month in which the payment date falls.

[7] See, for instance, Geert Bekaert and Campbell R. Harvey (1995) or Frank De Jong and Frans A. De Roon (2001).

robustness of the Sell in May effect. We consider market returns of Argentina, Brazil, Chile, Finland, Greece, Indonesia, Ireland, Jordan, Korea, Malaysia, Mexico, New Zealand, the Philippines, Portugal, Russia, Taiwan, Thailand, and Turkey. For these shorter series we have 128 monthly returns of MSCI reinvestment[8] indices (local currency) starting from 1988. For Russia we have 44 observations only. Table 1 contains some basic characteristics for all markets. In addition to the market return series above we also use long time series on stock market returns from Global Financial Data.

B. *Methodology*

To test for the existence of a Sell in May effect we used the usual regression techniques. We incorporated a seasonal dummy variable S_t in the regression:

$$(1) \quad r_t = \mu + \alpha_1 S_t + \varepsilon_t \qquad \text{with } \varepsilon_t = r_t - E_{t-1}[r_t]$$

where μ is a constant and ε_t the usual error term.

Note that in the absence of the dummy variable this equation reduces to the well-known random walk model.

The dummy variable takes the value 1 if month t falls on the period November through April and 0 otherwise. We tested whether the coefficient of S_t is significantly different from zero. When α_1 is significant and positive, this rejects the null hypothesis of no Sell in May effect. Due to the specific structure of the dummy variable, the regression equation is in fact a simple mean test: are mean returns during the period November–April significantly higher than during the period May–October? The advantage of using this regression is that one can easily include other variables, as we do later in this paper.

[8] Excluding dividends would only strengthen our results as in many countries there is a tendency to pay dividends in May through October.

C. *Results*

Figure 1 reports the average returns in the period May–October and the period November–April for each country. As can be seen in Figure 1, the differences in returns in the two half-year periods are generally very large and economically significant.[9] Returns over the period May–October tend to be close to zero in many countries. In Europe, with the exception of Denmark, average returns over this six-month period do not exceed 2 percent. However, during the period November–April they exceed the 8 percent in all European countries. While less pronounced, all other non-European countries in Figure 1 have higher returns in the period November–April than during the remainder of the year. Even in the United States the difference is substantial: on average, returns are more than 5 percent higher between November and April than they are during the remainder of the year.

In Figure 2 we plot the results for the shorter series in our database. We found that especially the European countries show a strong and economically significant seasonal pattern. Low returns between May and October, high returns between November and April. Moreover, the Sell in May effect seems also strongly present in many Asian countries. It is also present in Latin American countries, although differences in average returns between these periods are smaller. New Zealand is the only country where average returns are higher in May though October than during the remainder of the year.

Even though these results are economically significant, we should clearly be careful in assigning too much weight to these point estimates. The relevant question is whether these results are also statistically significant.

In Table 1 we report some summary statistics

[9] Transaction costs will hardly effect an investor who would trade on these results. For instance, assuming conservative transaction costs of 0.5 percent for a single transaction, the annual return would drop with approximately 1 percent. For a practical implementation of trading on this effect it would, however, be more appropriate to use index futures. In that case transaction costs are much lower. For instance, Bruno Solnik (1993) estimates the round-trip transaction costs of 0.1 percent on futures contracts.

TABLE 1—SUMMARY STATISTICS AND SELL IN MAY EFFECT

Countries	Number of Observations	Mean	Standard Deviation	α_1	t-Values of Sell in May Dummy (No January Effect)	t-Values of Adjusted Sell in May Dummy with January Effect	t-Values of January Dummy with Adjusted Sell in May Dummy
Argentina	128	7.95	26.72	0.51	0.11	0.35	−0.66
Austria	344	0.66	5.40	1.57	**2.71**	**2.89**	0.69
Australia	344	0.82	6.52	0.96	1.36	1.06	1.41
Belgium	344	1.18	4.73	2.31	**4.67**	**3.83**	**4.42**
Brazil	124	16.32	21.50	6.50	**1.70**	1.22	**1.78**
Canada	344	0.83	4.99	1.14	**2.12**	**1.80**	**1.65**
Chile	128	2.21	7.47	1.49	1.13	0.76	1.30
Denmark	344	1.10	4.95	0.34	0.64	−0.48	**3.49**
Finland	128	1.24	8.16	2.20	1.54	0.99	**2.56**
France	344	1.03	6.02	2.31	**3.62**	**3.12**	**2.89**
Germany	344	0.78	5.30	1.38	**2.44**	**2.23**	**1.68**
Greece	128	2.12	10.80	3.34	**1.77**	1.53	1.40
Hong Kong	344	1.40	10.89	0.84	0.72	0.13	**2.18**
Indonesia	128	1.39	13.12	2.67	1.15	0.86	1.58
Ireland	128	1.25	5.83	2.60	**2.57**	**1.76**	**3.79**
Italy	344	0.91	7.13	2.70	**3.56**	**2.56**	**4.57**
Japan	344	0.70	5.42	1.52	**2.62**	**2.23**	**2.19**
Jordan	128	0.56	4.39	1.05	1.36	1.03	1.45
Korea	128	−0.18	9.29	1.03	0.62	−0.10	1.47
Malaysia	128	0.15	8.66	2.59	**1.71**	**1.87**	0.15
Mexico	128	2.82	9.41	1.26	0.76	0.78	0.24
Netherlands	344	1.12	4.95	1.88	**3.58**	**2.91**	**3.35**
New Zealand	128	0.39	6.34	−0.45	−0.40	−0.56	0.36
Norway	344	0.93	7.56	1.23	1.51	0.68	**3.19**
Philippines	128	0.87	9.02	2.64	**1.67**	1.51	1.23
Portugal	128	0.83	6.36	1.65	1.48	1.00	1.62
Russia	44	−0.94	24.47	2.40	0.32	0.53	−0.30
Singapore	344	0.67	8.39	1.84	**2.05**	1.25	**2.80**
South Africa	308	1.34	7.50	0.76	0.89	1.25	−0.48
Spain	344	1.06	6.04	1.88	**2.92**	**2.31**	**2.96**
Sweden	344	1.39	6.15	2.17	**3.32**	**2.60**	**3.33**
Switzerland	344	0.82	5.00	1.08	**2.01**	1.45	**2.36**
Taiwan	128	0.78	12.24	5.57	**2.63**	**2.48**	1.45
Thailand	128	0.01	11.20	2.73	1.39	0.90	**1.80**
Turkey	128	5.18	16.07	1.81	0.63	0.01	**1.85**
United Kingdom	344	1.17	6.12	2.02	**3.10**	**2.48**	**2.45**
United States	344	0.96	4.42	0.93	**1.95**	1.61	1.61

Notes: Summary results on value-weighted MSCI reinvestment indices for several countries. Monthly mean returns as percentage, monthly standard deviation as percentage, α_1 refers to the parameter of regression of equation (1) and is reported as a percentage. In addition we report related t-values based on heteroskedasticity-consistent standard errors. We report t-values for Sell in May (unadjusted and adjusted) and January dummies in regressions (1) and (2) in the text. Column six contains the results of the regression with only the Sell in May dummy. Columns seven and eight contain t-values of a regression with an adjusted Sell in May dummy (value zero in January and one in the other November through April months) and a January dummy combined.

and some basic estimation results from equation (1). α_1 denotes the average monthly returns in the period November–April in excess of the average monthly returns during the other six months of the year. Thus the simple test as to whether mean returns are higher during the period November–April than during the period May–October. Table 1 shows that in 20 of the 37 countries there is a statistically significant Sell in May effect present at the 10-percent

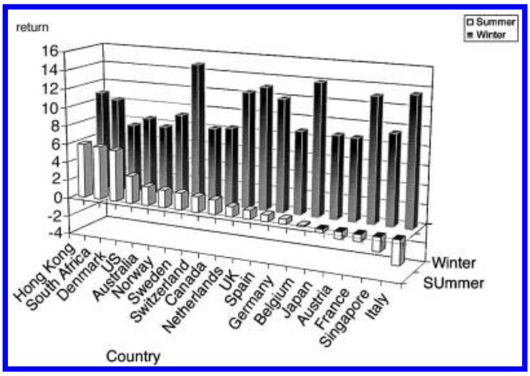

FIGURE 1. RETURNS IN SUMMER AND WINTER

Notes: Average returns (as percentage) in May–October (Summer) and November–April (Winter) in several countries. MSCI reinvestment indices 1970–August 1998.

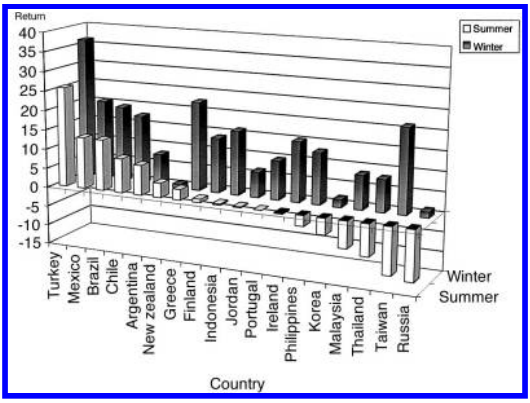

FIGURE 2. SELL IN MAY EFFECT IN EMERGING MARKETS

Notes: Emerging Markets: Average Returns in May–October (Summer) and November–April (Winter) in several emerging markets. MSCI reinvestment indices 1988–August 1998. Due to scaling, the reported values for Argentina and Brazil are average *monthly* returns in the two periods. The other returns are—as before—average returns over the six-month period.

level (t-value of 1.65). The effect is highly significant—for 10 countries in our sample it remains significant at the 1-percent level.[10]

D. *Monthly Returns: Breaking Down the Results by Months*

An interesting question that arises is whether these low returns during the period May–October are more or less evenly spread over these months in all countries, or whether they can be attributed to specific months. In Table 2 we report the difference between average monthly returns and the annual average returns in all countries. The countries are listed according to the relative strength of the Sell in May effect using the t-values in Table 1.

In general, returns tend to be below average in all months from May through to October, although results tend to be mixed for July. In almost all countries, August and September are especially bad months for stock markets.

E. *Persistence over Time*

Is the Sell by May effect a recent phenomenon, or has it been noticeable in the past? To answer this question we considered monthly total return indices for all stock markets for which we could obtain substantially longer time series than the previously considered MSCI indices. For 11 countries we were able to obtain monthly stock returns that include dividends from Global Financial Data.[11] The longest

[10] The results in Table 1 show that contrary to other anomalies this Sell in May effect is not only significantly present in many developed markets but also in many emerging markets. Due to the high correlation between these markets we might be measuring the same effect in the world over and over again. We first checked whether this effect is significantly present in the World Market index. Indeed, this index exhibits a significant Sell in May effect (at the 1-percent level). However, even when we include the return on the MSCI World Market index as an additional explanatory variable in the regression (1), we find a significant Sell in May effect (at the 10-percent level) in 9 (mostly European countries) of the 19 developed countries for which the series start in 1969. Without this explanatory variable, we find a significant effect in 14 of these 19 countries. If we jointly estimate the equation (1) with the World Market index included for these markets, a joint Wald test rejects the hypothesis that all dummy coefficients equal zero ($\chi^2(19) = 39.56$, p-value of 0.0037). Without the market index a joint Wald test also rejects the hypothesis that all dummy coefficients equal zero ($\chi^2(19) = 48.85$, p-value of 0.00019). This suggests that the effect is mostly country specific.

[11] An extensive description of all these series is available on the website of Global Financial Data: www.globalfindata.com/gtotal.txt.

TABLE 2—AVERAGE MONTHLY RETURNS

Country	Jan.	Feb.	March	April	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.	Mean	t-Value
Belgium	2.7	1.4	0.5	1.4	−2.3	−0.5	0.7	−2.1	−1.5	−1.4	−0.1	1.0	1.2	**4.67**
France	2.4	1.4	1.3	1.6	−1.1	−2.5	0.5	−0.7	−1.7	−1.5	−0.2	0.3	1.0	**3.62**
Netherlands	2.5	−0.2	1.7	1.0	−0.7	−0.2	1.0	−1.6	−2.7	−1.6	−0.6	1.1	1.1	**3.58**
Italy	4.9	1.6	1.5	0.6	−1.6	−2.3	−0.2	0.1	−2.1	−2.1	−0.8	0.1	0.9	**3.56**
Sweden	3.1	1.8	0.8	−0.1	−0.4	−0.6	2.0	−3.7	−2.4	−1.4	0.4	0.4	1.4	**3.32**
United Kingdom	3.1	0.8	−0.3	1.9	−1.4	−1.5	−0.1	0.0	−1.6	−1.6	−0.8	1.3	1.2	**3.10**
Spain	2.6	1.9	0.5	0.9	0.7	−0.3	−0.7	−1.0	−2.7	−1.7	0.3	−0.7	1.2	**2.92**
Austria	0.0	2.3	0.1	0.6	0.0	−0.7	0.3	−1.4	−1.3	−1.7	−0.4	2.1	0.7	**2.71**
Taiwan	3.2	6.8	−1.2	2.4	−2.0	−2.0	0.6	−6.0	−2.4	−5.2	2.8	2.7	0.8	**2.63**
Japan	1.5	0.1	1.0	0.6	0.0	−0.5	−0.1	−1.4	−1.3	−1.3	−0.2	1.6	0.7	**2.62**
Ireland	5.0	1.9	0.8	0.7	−0.6	−0.9	0.9	−3.5	−2.7	−1.0	−2.5	1.6	1.3	**2.57**
Germany	1.1	1.0	1.1	0.0	−1.6	0.3	1.0	−1.4	−1.6	−0.9	−0.1	1.0	0.8	**2.44**
Canada	1.3	0.9	−0.2	−1.1	0.3	−0.6	0.5	0.0	−1.9	−1.8	0.8	1.8	0.8	**2.12**
Singapore	4.3	1.2	−1.2	−0.4	1.8	−0.8	−1.1	−3.1	−1.6	−0.8	−1.1	2.7	0.7	**2.05**
Switzerland	2.0	−0.3	0.4	−0.6	−0.8	0.9	0.2	−1.4	−1.9	−0.2	0.1	1.7	0.8	**2.01**
United States	1.2	0.0	0.0	0.1	−0.2	0.1	−0.2	−0.7	−1.3	−0.6	0.6	0.9	1.0	**1.95**
Greece	3.3	4.5	1.1	3.4	−2.3	1.1	2.2	−3.5	−1.1	−6.9	−3.8	0.9	2.1	**1.77**
Malaysia	−0.9	6.6	−1.2	−0.1	0.3	−1.4	−0.5	−7.0	0.3	0.8	−2.1	5.6	0.2	**1.71**
Brazil	11.3	3.4	−6.3	3.9	−1.4	−9.5	3.1	−5.2	4.0	−11.1	−5.5	12.1	16.3	**1.70**
Philippines	2.0	2.1	−1.0	1.7	2.9	−1.7	0.8	−7.2	−3.5	0.8	−0.9	4.1	0.9	**1.67**
Finland	4.6	1.9	0.0	3.0	0.5	−1.7	3.3	−5.2	−3.8	0.1	0.3	−3.7	1.2	1.54
Norway	3.9	−1.2	−0.9	3.2	0.3	−0.5	2.0	−1.2	−2.4	−1.9	−2.0	0.6	0.9	1.51
Portugal	3.5	2.5	1.3	−1.0	−0.4	−1.7	0.6	−1.0	−0.7	−2.0	−1.1	−0.4	0.8	1.48
Thailand	6.0	1.2	−0.9	1.1	−1.4	−1.6	2.7	−5.7	−1.0	−1.2	−3.6	4.3	0.0	1.39
Australia	1.5	−1.0	0.3	1.2	0.6	−1.0	0.7	0.0	−1.6	−1.5	−1.4	2.4	0.8	1.36
Jordan	1.5	−1.6	−1.0	0.8	1.0	−0.3	−1.2	−2.8	0.9	−0.7	0.7	2.9	0.6	1.36
Indonesia	3.9	1.9	1.1	−3.2	3.6	−1.8	−0.5	−1.4	−6.4	−2.1	−4.0	8.4	1.4	1.15
Chile	3.0	3.3	−2.4	−0.9	−0.2	1.7	−0.4	−4.5	−0.6	−0.5	−1.3	2.8	2.2	1.13
South Africa	−1.2	0.3	1.4	−0.2	0.5	−0.9	1.7	−1.1	−0.9	−1.3	0.1	2.2	1.3	0.89
Mexico	0.1	−0.9	2.7	−1.3	4.0	−2.5	1.3	−3.5	−2.8	−0.5	2.8	0.5	2.8	0.76
Hong Kong	3.8	2.9	−3.4	−0.3	2.1	−0.4	0.9	−2.8	−2.9	0.6	−3.9	3.4	1.4	0.72
Denmark	3.2	−1.1	−1.7	0.4	0.4	0.9	0.7	−1.9	−1.6	0.5	−1.5	1.7	1.1	0.64
Turkey	9.5	−1.4	−4.9	0.1	−2.4	6.4	−5.5	−6.2	6.7	−4.0	−1.3	3.4	5.2	0.63
Korea	6.2	−2.5	−0.7	0.0	−0.7	−3.8	2.7	−2.3	1.4	−0.3	0.2	−0.2	−0.2	0.62
Russia	−5.6	0.8	3.5	3.9	6.3	17.2	−2.1	−21.2	−2.1	−6.9	−7.5	12.9	−0.9	0.32
Argentina	−5.6	4.2	3.4	3.2	10.2	1.1	−3.5	−0.2	3.2	−13.1	−11.0	7.0	8.0	0.11
New Zealand	0.8	−2.0	0.0	2.3	1.6	−1.4	3.8	−0.5	−2.5	0.2	−1.8	−0.8	0.4	−0.40

Notes: Differences between average returns in each specific month and the monthly average returns over all months for every country. All returns measured as percentage. Countries ordered descending by the t-value of the Sell in May effect taken from Table 1.

series is the return series for the United Kingdom that begins with September 1694. To prevent overlap with the MSCI indices, we reestimated the regression in (1) where we use December 1969 as the end date of all samples. The starting date of our samples were simply the starting dates of the series. The results are reported in Table 3.

In all countries except Australia, returns are higher during the period November–April than during the remainder of the year. In 4 of the 11 countries this result is significant at the 10-percent level, and in 3 out of 11 countries it is significant at the 5-percent level. This would lead one to believe that the Sell in May effect has been present in the data for a very long time, although results tend to be less significant now than in the last 30 years.

F. *Trading Strategies*

From a practical point of view it is interesting to consider how a trading strategy based on this simple market wisdom would perform in com-

TABLE 3—SELL IN MAY IN THE LONG RUN

	Starting Date of Series	Constant Estimate	Constant t-Value	Sell in May Dummy Estimate	Sell in May Dummy t-Value
Australia	1882:09	1.044	8.20	−0.066	−0.39
Belgium	1950:12	0.520	1.81	0.384	0.99
Canada	1933:12	0.523	1.87	0.774	**2.11**
France	1900:01	0.748	2.68	0.601	1.42
Germany	1926:01	0.823	1.85	0.630	1.23
Italy	1924:12	1.283	2.66	0.239	0.33
Japan	1920:12	0.804	2.52	1.306	**2.29**
Netherlands	1950:12	0.640	1.69	1.125	**2.17**
Spain	1940:03	0.966	3.39	0.386	0.89
United Kingdom	1694:09	0.393	5.22	0.196	**1.85**
United States	1802:01	0.632	1.72	0.169	0.84

Notes: Out-of-sample evidence: long time series of monthly stock returns. We report parameter estimates and t-values (based on heteroskedasticity-consistent standard errors) for the constant (in percent) and the Sell in May dummy (in percent) in regression (1). Estimates are based on data availability, but all samples end December 1969 to prevent overlap with the MSCI data.

parison with a simple buy and hold strategy. In the Appendix we carry out this comparison in more detail. We show that in most countries we can reject the null hypothesis that the risk-free asset and the market index span the annual returns of this trading strategy (i.e., we reject mean variance efficiency of the index). Moreover, we find that this trading strategy has significant market-timing potential in the Roy D. Henriksson and Robert C. Merton sense (1981).

II. Possible Explanations for the Puzzle

How can we best explain these results? In the past, academic research has offered a series of possible explanations for this type of finding, such as the lack of economic significance, data mining, or risk differences (see also Grant McQueen and Steven Thorley, 1999). Here we consider all these possible explanations in some detail. The financial press has also suggested several explanations and possible causes,[12] and although at first sight some of these might seem implausible, we also consider their merits. Further popular explanations are related to changes in the fundamental factors that drive the economy, and therefore suggest that this anomaly is sector specific. For instance, one explanation relates this effect to the agricultural sector and another to the consumer goods industry. Still other explanations cite (the summer) vacation and its possible consequences on trading. And one English newspaper formulates its explanation as follows:

> Historically, the summer fall was caused by farmers selling and sowing their crops and rich investors swanning off to enjoy Ascot, the Derby, Wimbledon, Henley and Cowes. Modern investors jet off to the Med, where they cannot find copies of their pink papers and senior fund managers soak up the sun on Caribbean cruises leaving their nervous second-in-commands in charge (*Evening Standard*, May 26, 1999).

A. *Economic Significance*

Many so-called anomalies can easily be explained by introducing transaction costs. In the case of some "anomalies," their continued existence can be explained by the simple fact that the potential benefits do not outweigh the cost of trading—in which the Monday effect is a clear example. However, as we have already seen (in the Appendix), if one assumes reasonable transaction costs the Sell in May effect remains economically significant.

B. *Data Mining*

The Sell in May effect differs from other calendar anomalies. Other calendar anomalies like the January effect or the Monday effect could well be caused by data mining. Just like the finding of unpredictability in empirical research ultimately lead to the efficient market hypothesis, these anomalies are not preceded by any theory or indication that would have investors believe that Mondays or the month of January are special. In addition, possible theories for the existence of these anomalies were introduced after the empirical finding.

While we lack a formal theory, we do at least have an old market saying to go by. In other words, we have not tried all half-year periods and have only reported the results of the best period we could find. And we used one half-year period only, based on the Sell in May

[12] Details on all tests and results can be obtained from the authors.

saying in combination with the Halloween indicator. Moreover, at the beginning of our main sample investors could have been well aware of the existence of this anomaly. Another test to prevent data mining is to consider out-of-sample results. In the case of a pure data-driven anomaly one would expect the results to hold only in a few countries and only over short periods of time. However, our results are robust with respect to the countries we considered, and consistent over extremely long periods of time in several countries. For this reason we ultimately reject data mining as a possible explanation of our findings.

C. *Risk*

Another natural question to ask is whether these results are risk related. Are higher returns during the period November–April a compensation for a higher risk in this period? The answer is likely to be no. Risk, measured by the standard deviation, tends to be similar in both periods and throughout the year. In Table 4 we illustrate (annualized) risk and returns in the two subperiods.

This table reveals some interesting insights. While returns differ considerably, the standard deviation in the two periods remains fairly constant. In a number of countries (Belgium, Brazil, Chile, Hong Kong, Japan, Jordan, Singapore, Sweden, Turkey, and the United Kingdom) the standard deviation is higher in November–April than it is during May–October, but in most of these countries the difference is only marginal. It seems unlikely that these results would justify the difference in returns. For instance, in the Swedish market investors would require an additional risk premium of more than 25 percent to compensate them for an increase in standard deviation of only 0.2 percent.[13] In all other countries, risk tends to be higher during the period May–October, while returns are lower.

[13] Modeling time-varying volatility more explicitly by use of a GARCH(1,1) model and a GARCH(1,1) in mean process for daily data in an earlier draft of this paper, we reached a similar conclusion.

TABLE 4—RISK AND RETURN

	November–April		May–October	
Countries	Mean	Standard Deviation	Mean	Standard Deviation
Argentina	98.5	86.0	92.4	99.3
Australia	15.6	19.7	4.1	25.1
Austria	17.3	17.7	−1.5	19.3
Belgium	28.0	16.0	0.3	15.8
Brazil	233.6	82.7	155.6	63.2
Canada	16.8	16.6	3.1	17.8
Chile	35.4	26.2	17.5	25.5
Denmark	15.2	16.5	11.1	17.8
Finland	28.1	25.1	1.6	30.9
France	26.2	19.4	−1.5	21.5
Germany	17.6	16.5	1.0	19.8
Greece	45.5	35.2	5.4	38.9
Hong Kong	21.9	38.0	11.8	37.5
Indonesia	32.7	42.2	0.7	48.4
Ireland	30.6	18.8	−0.5	20.7
Italy	27.1	22.1	−5.2	26.3
Japan	17.6	19.3	−0.7	17.8
Jordan	13.0	15.2	0.4	15.1
Korea	4.0	32.2	−8.3	32.3
Malaysia	17.4	28.8	−13.7	30.7
Mexico	41.4	32.3	26.3	33.0
Netherlands	24.7	15.7	2.1	17.9
New Zealand	2.0	20.8	7.5	23.2
Norway	18.6	25.0	3.8	27.3
Philippines	26.3	28.7	−5.4	33.3
Portugal	19.8	20.3	0.0	23.4
Russia	3.1	64.6	−25.6	102.5
Singapore	19.1	29.2	−3.0	28.7
South Africa	20.7	24.2	11.5	27.6
Spain	24.0	19.8	1.5	21.5
Sweden	29.7	21.1	3.7	20.9
Switzerland	16.3	15.2	3.3	19.1
Taiwan	42.7	41.2	−24.1	41.7
Thailand	16.5	34.1	−16.3	42.7
Turkey	73.0	59.7	51.3	51.6
United Kingdom	26.2	22.0	1.9	19.9
United States	17.1	14.0	6.0	16.4
World market	19.9	14.1	4.6	14.7

Notes: Risk and return in the period November–April and in the period May–October measured by annualized standard deviation (in percent) and annualized mean (in percent) respectively. All results are based on the MSCI value-weighted reinvestment indices.

D. *Sell in May and the January Effect*

The Sell in May hypothesis suggests that average returns are higher during the period November to April than during the period May to October. However, one might argue that since the January effect generates high positive returns in many stock markets, the Sell in May effect is simply the January effect in disguise. To test this possibility, we considered an additional regression. We now gave the Sell in May dummy the value 1 in the period November to April, except in January. In January we now assigned to this adjusted Sell in May dummy the value 0. In addition we included a January dummy:

$$(2) \quad r_t = \mu + \alpha_1 S_t^{adj} + \alpha_2 Jan_t + \varepsilon_t \quad \text{with } \varepsilon_t = r_t - E_{t-1}[r_t]$$

in which Jan_t denotes the January dummy that takes the value 1 when returns fall in January and 0 otherwise. By estimating this regression, we accepted the point that all excess returns in January (above the average returns in May through October months) are entirely due to a January effect and not caused by a Sell in May effect. Note that this might exaggerate the size of the January effect and might in addition understate the "true" size of the Sell in May effect. For instance, in countries without a significant January effect but with a strong Sell in May effect, we might now find a significant January effect.[14] The t-values for the parameters of the dummy variables in this additional regression are reported in Table 1 (columns seven and eight). We found that in many countries the Sell in May effect cannot be a January effect only. Column seven shows that the Sell in May effect measured in this way survives this test in 14 out of 20 countries were we found a significant Sell in May effect previously. The t-values in column eight also confirmed the conclusion of Claessens et al. (1995) that the January effect is not strongly present in emerging markets. We therefore reject the hypothesis that the Sell in May effect is the January effect in disguise.[15]

E. *Interest Rates and Trading Volume*

Can the difference in returns between the May–October months and the November–April months be caused by shifts in either interest rates or by shifts in trading volume?[16] If for some reason central banks have a tendency to lower interest rates during the latter period or raise interest rates between May and October, this might explain this puzzle. Moreover, if there are large shifts in trading volume—because investors trade on average less frequently during May through October than during the other part of the year—this could also provide us with some clues. We tested whether interest rates are significantly higher during the period May–October than during the period November–April. We also considered whether trading volume is substantially lower or higher during the summer than during the winter. However, we found no evidence that interest rates are significantly higher during the May–October period in any of these countries. While in most cases t-values are negative (implying somewhat lower interest rates during November through April), in no country is this difference statistically significant.[17] Trading volume tends to be somewhat higher during November–April in most countries in our sample, but in no country is this difference statistically significant. All in all there seems little evidence to suggest that the

[14] To be precise, if we only use a dummy for the January effect we find a significant January effect in 16 countries (at the 10-percent level). In the specification above we find a significant January effect in 20 countries. The four additional countries where we find the January dummy to be significant—Brazil, Canada, Germany and Japan—do show a strong Sell in May effect. Moreover if we estimate regression (2) with an unadjusted Sell in May dummy we find a significant January effect in 13 countries.

[15] Including a dummy variable for the stock market crash of 1987 or excluding October 1987 from our data set does not change our results either.

[16] These interest rate and volume series are taken from Datastream.

[17] We also tested for significant changes in interest rates in April or May but found none. Moreover, note that changes in interest rates need not be significant to cause this effect. Therefore, we jointly estimate for the developed markets (the 16 countries for which we have data) whether the Sell in May effect in the index returns disappeared if we, in addition to the return on the world market and the January dummy, include the interest rate as an explanatory variable in our regression. However, also adding the interest rate does not seem to explain the Sell in May effect: a joint Wald test that all dummy coefficients equal zero was rejected ($\chi^2(16) = 32.70$, p-value of 0.00809).

Sell in May effect is related to interest rates or trading volume.

F. *Sectors*

Is the Sell in May puzzle a sector-specific anomaly, or does it manifest itself in all sectors of the economy? This is an important question because if the anomaly is not sector specific, we should look to macroeconomic factors to explain it.

According to the agricultural hypothesis,[18] farmers take on credit during late spring and early summer to buy sowing seed. This higher demand for credit then leads to an increase in interest rates and a lack of liquidity in the market. These two factors then drive the market down. In autumn, when the crops are harvested and sold and loans are repaid, the interest rate drops and liquidity increases.

While we had already rejected the idea that this puzzle can be explained by changes in either interest rates or trading volume, we can test more directly whether or not return differences are related to, for instance, the agricultural sector.[19] If this explanation were true, one would expect that the effect would be particularly strong in countries with a large agricultural sector. We found no significant relation between the size of the Sell in May effect (corrected for differences in risk between countries) and the size of the agricultural sector. If anything, this relation is a negative one. The smaller the size of the agricultural sector, the larger the Sell in May effect.

Despite this, the question remains as to whether the Sell in May effect is a general or a sector-specific phenomenon. To test this, we once again relied on cross-sectional data for the different countries. As with the agricultural sector, we first investigated whether differences in sizes between the different countries are related to the size of the anomaly. We found no evidence that the Sell in May effect is related to the relative sizes of specific sectors in the different economies. In all cases *t*-values indicated that the parameter related to the size of the different sectors is not significantly different from zero. These results are robust when we considered an "outlier corrected" regression, where we dropped the two most extreme observations.

As a second test with regard to whether the anomaly is sector specific, we analyzed returns on sector indices directly. Given the fact that these sector indices might contain a large country-specific component, the approach is somewhat more complicated. For a large number of markets Datastream reports different sector-specific indices. The main sectors that Datastream defines are Resources, General Industries, Consumer Goods, Services, Utilities, and Financials. We used an estimate for every sector regression (1) to test for the existence of a Sell in May effect in these sectors. The main problem with these estimates is that they also contain a country effect, i.e., if a country already shows a strong Sell in May effect, all sector indices in this country are also likely to exhibit the effect. We corrected for this country effect and differences in the risk of different sectors. Again, these results confirmed our earlier finding that the effect is not related to specific sectors.

G. *Vacations*

One thing we did find was that the size of the effect is significantly related to both length and timing of vacations and also to the impact of vacations on trading activity in different countries. We approximated the length of vacations in different countries by the length of paid annual leave and the number of public holidays[20] (public holidays measured during the year and in the period May–October only). The percentage of outbound travel in each country during May–October (related to total outbound travel in that country)[21] approximates the timing of vacations within the year. We also linked this proxy on a monthly basis to stock returns, and found that the monthly level of outbound travel is inversely and significantly related to monthly levels of stock returns. Finally, we approxi-

[18] Suggested by a journalist of the German magazine *Die Welt*.

[19] Sector returns series are from Datastream, sector sizes from Encarta World Atlas.

[20] Data from the International Labour Organization and Encarta World Atlas.

[21] Data from the World Tourism Organization.

mated the impact of vacations on trading activity by total outbound travel during the summer as a percentage of the total population multiplied by total market turnover per capita.[22] We then found a significant relation between our proxy and the effect in different countries.

It is fairly easy to construct a theoretical model that links vacations to this effect using the following intuition. Investors in the economy bear the financial risk in the economy. When there is either an unanticipated (negative) shift in the number of investors or when there is an unanticipated change (positive) in risk aversion, the risk-bearing capacity in the economy decreases and the remaining investors are only willing to bear the risk if they receive a higher risk premium. This will drive prices down during the period when such a shift occurs, to create higher expected returns.

A forceful argument against this model is arbitrage. Smart investors would realize that there are (risky) arbitrage opportunities and this would make them short lived.[23]

An alternative explanation could be that investors feel financially constrained after their vacation because they have spent more during a vacation than they would in their working life. In that case they might demand a higher liquidity premium during the winter. This might also result in an empirical link. Once again, however, arbitrage (by investors who do not face liquidity constraints) would make the effect disappear. A final problem with this link is that it should affect northern and southern hemispheres differently. If summer vacations are indeed the cause of a Sell in May effect, one would expect the opposite effect in countries on the Southern Hemisphere. We do not find this. In fact, we find that the countries on the Southern Hemisphere (Argentina, Australia, Brazil, Chile, New Zealand, and South Africa) also have higher returns during the period November–April (with the exception of New Zealand), although these differences are not statistically significant.

H. *News*

Are stock returns lower during May to October because of a seasonal factor in the provision of news? If more negative news about the economy appears between May and October than during the remainder of the year, this would explain the low or negative returns during this period. Either by coincidence or due to some unknown reason, there might be some seasonal factor in the information that reaches the market. We investigated this issue in the following way. In the Dutch financial newspaper *Het Financieele Dagblad* we counted the number of times the words "positive," "negative," "optimism," and "pessimism" (which in Dutch are similar to the English words[24]) are used in the different months, and counted word frequency over the period 1985–1998. If there is indeed a strong seasonal factor one would expect that the words "negative" and "pessimism" would occur more frequently during the May–October period, with the reverse being true for the words "positive" and "optimism." We first investigated whether there is a relation between news and stock returns by linking monthly stock returns with respective monthly word frequencies. If such a relation exists we would expect the estimates of the parameters related to the variables "positive" and "optimism" to be significantly positive and the estimates of the parameters related to "negative" and "pessimism" to be significantly negative. We found that this is indeed the case. The next question is whether there is a seasonal factor in news, and if so whether it can explain the observed effect. To answer these questions we first ran four regressions like equation (1) where we included a seasonal Sell in May dummy. As our dependent variable we now used monthly word frequency instead of returns. The result,

[22] Data taken from the IFC Factbook.

[23] As one referee put it: "Cleary those who sell by end of April and buy back by end of October have an apparent gain—they do not have to bear any risk and in addition they are also not giving up reward. Then everyone should be engaging this strategy."

[24] The Dutch translations are "positief," "negatief," "optimisme," and "pessimisme."

however, was that we found no seasonal factor in news.

III. Conclusions

Based on the old market saying "Sell in May and go away" (or the Halloween indicator), we find that there is a substantial difference between returns in the period May–October and the remainder of the year. In fact our evidence shows that while during the period November–April returns are large in most countries, average returns in the period May–October are not significantly different from zero and are often even negative.

We investigated several possible causes for this Sell in May effect and are able to rule out the usual explanations such as data mining, the January effect, and risk explanations. Our results also reject the idea of some less likely explanations such as shifts in interest rates or in volume. Nor do we find that the effect is caused by sector-specific factors as suggested in the popular press.

We do find that there is a positive and significant relation between our three proxies for the length and timing of summer vacations, and the impact of vacation on trading activity and the Sell in May effect. With respect to the timing of vacations, we found that this significant relation holds at both the monthly and the half-yearly level. However, we also showed that arbitrage is a forceful argument against this empirical link. So we are faced with the following problem: history and practice tells us that the old saying is right, while stock market logic tells us it is wrong. It seems that we have not yet solved this new puzzle.

APPENDIX

We compare annual returns of two trading strategies: the Halloween strategy and a Buy and Hold strategy:

- *Halloween strategy:* We assume that an investor who would like to profit from a Sell in May effect decides to buy a market portfolio at the end of October and sells this portfolio at the beginning of May. This investor will then invest in a risk-free asset (short-term Treasury bonds)[25] from the end of April through to the end of October.
- *Buy and Hold strategy:* This strategy holds the stock market portfolio throughout.

Table A1 contains the average annual returns and the standard deviation of the Buy and Hold strategy and the Halloween strategy. These results show that the Halloween strategy outperforms the Buy and Hold strategy in all countries except Hong Kong and South Africa. The standard deviation of the Halloween strategy is substantially lower than the standard deviation of the Buy and Hold strategy in all countries. These results are confirmed when we compare cumulative frequency distributions of the two different strategies. Here, in Figure A1, we only plot the cumulative frequency distribution for Italy. However, similar results, though somewhat less pronounced, are obtained for other countries.

An important question is whether these results are statistically significant. There are sev-

[25] In this Appendix we use (continuously compounded) monthly stock returns of value-weighted market indices of 17 countries (local currencies) and a World Market index (in U.S. dollars). The countries analyzed are: Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Ireland, Italy, Japan, The Netherlands, Singapore, South Africa, Switzerland, the United Kingdom, and the United States. All series are taken from Datastream. They consist of 288 observations over the period January 1973 through December 1996 and include dividends. As these results are derived from an earlier draft of the paper the ending date is not August 1998. We used monthly short-term interest rates (interbank or Treasury bill rates) taken from either the OECD or the IMF. We used IMF interest rates when these rates are available for the full sample period, otherwise we take OECD short-term interest rates. For Switzerland we had to construct a time series of interest rates from both sources as they were not available over the full sample. For Singapore we used the discount rate. For Hong Kong we used a national source: Hong Kong savings deposit rate (paid). As noted by Solnik (1993) the type of interest rates reported by the OECD tend to be different across countries. Therefore we checked our results for most countries using six months Eurocurrency interest rates. Unfortunately these are only available since 1981. However, the results obtained with the Eurocurrency rates were qualitatively similar to the results reported here. More detailed information on the interest rates is available on request from the authors.

TABLE A1—BUY AND HOLD VERSUS HALLOWEEN

	Buy and Hold Strategy		Halloween Strategy	
Country	Mean	Standard Deviation	Mean	Standard Deviation
Australia	12.12	25.15	13.90	14.52
Austria	8.62	26.39	11.69	17.11
Belgium	10.62	19.39	16.00	11.61
Canada	10.22	14.36	12.48	11.20
Denmark	12.15	27.15	12.55	12.05
France	13.35	26.90	17.81	16.13
Germany	8.99	21.69	10.84	12.33
Hong Kong	15.06	41.92	12.81	30.85
Ireland	15.12	34.68	18.31	21.41
Italy	13.05	28.44	19.72	16.45
Japan	7.14	19.90	9.46	16.39
Netherlands	12.73	18.66	15.15	11.24
Singapore	7.62	34.99	12.74	31.75
South Africa	18.80	22.96	15.14	15.97
Switzerland	7.51	22.06	8.09	14.18
United Kingdom	14.86	28.18	18.84	21.48
United States	11.37	16.40	11.61	11.38
World index	10.92	16.76	12.47	12.58

Note: Average annual returns (as percentage) and standard deviations (as percentage) of a Buy and Hold strategy and the Halloween strategy over the years 1973 through 1996.

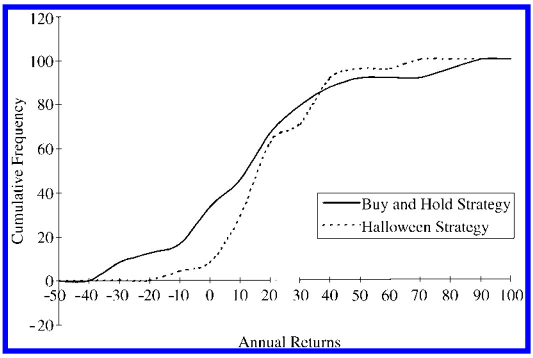

FIGURE A1. CUMULATIVE FREQUENCY DISTRIBUTIONS

Notes: Cumulative frequency distributions and annual returns are in percentages. Cumulative frequency distributions for the Italian market for the Buy and Hold strategy and the Halloween strategy based on annual returns (as percentage) over the years 1973–1996.

TABLE A2—ESTIMATION RESULTS

Country	α	β
Australia	0.031	0.396
	[1.24]	[4.17]
Austria	0.041	0.55
	[2.39]	[6.70]
Belgium	0.069	0.547
	[4.76]	[8.48]
Canada	0.033	0.543
	[1.70]	[5.08]
Denmark	0.015	0.389
	[1.17]	[9.35]
France	0.070	0.503
	[3.01]	[6.85]
Germany	0.032	0.431
	[2.18]	[4.90]
Hong Kong	0.020	0.606
	[0.55]	[6.44]
Ireland	0.054	0.570
	[2.56]	[6.70]
Italy	0.089	0.232
	[2.41]	[1.89]
Japan	0.037	0.751
	[2.30]	[9.05]
Netherlands	0.056	0.568
	[4.36]	[6.81]
Singapore	0.048	0.721
	[1.24]	[5.14]
South Africa	0.017	0.343
	[0.75]	[3.18]
Switzerland	0.018	0.566
	[1.33]	[6.65]
United Kingdom	0.054	0.761
	[1.91]	[8.94]
United States	0.016	0.616
	[1.10]	[8.45]
World index	0.027	0.664
	[1.71]	[7.01]

Notes: Estimation results for the regression: $.0r_t^p - r_t^f = \alpha + \beta(r_t^m - r_t^f)_t + \varepsilon_t$. r_t^p denotes the return of the Halloween strategy in year t; r_t^f denotes the risk-free rate in year t; and r_t^m denotes the return on the index in every country. We report t-values based on heteroskedasticity-consistent standard errors in square brackets. Regressions are based on annual observations over the period 1973–1996.

eral ways to test the statistical significance of these findings. Here we first test whether we are able to reject the mean variance efficiency of the indices in the different countries. More specifically we use:

$$\text{(A1)} \quad r_t^p - r_t^f = \alpha + \beta(r_t^m - r_t^f) + \varepsilon_t \quad \text{with } \varepsilon_t = r_t^p - E_{t-1}[r_t^p]$$

in which r_t^p denotes the return in year t on the Halloween strategy in each country; r_t^f denotes the risk-free rate in year t; and r_t^m denotes the return on the index in every country. Table A2 contains the estimation results.

As the null hypothesis that α (Jensen's alpha) should be equal to zero is frequently rejected, this shows that in most countries mean variance efficiency of the stock market index is rejected. The estimates of β are well below 1. This confirms our conclusion that the Halloween strategy is substantially less risky than investing in the market index in the respective countries.

Another way to test whether the Halloween indicator has forecasting power is to investigate the market-timing ability of the Halloween strategy. Merton (1981) and Henriksson and Merton (1981) developed a (nonparametric) test for evaluating the market-timing ability of investment managers.[26] In their analysis, the investor predicts when stocks will out- or underperform bonds, but does not predict the magnitude of the superior performance.[27] The probability of a correct forecast, given that the stock return is below the risk-free rate, is defined as p_1, and the probability of a correct forecast, given that the stock return is above the risk-free rate, as p_2.

We analyzed whether the Halloween strategy has significant market-timing ability. The analysis takes into account the possibility that forecasting skills are different for bull markets and for bear markets. The Halloween strategy predicts that Treasury bills will outperform the stock market in the period ranging from May to October, and that the stock market will outperform in the remaining period each year. The results of the nonparametric test for 17 countries and the World index are set out in Table A3 for the period between 1973 through 1996. The null hypothesis of no market-timing ability is $p_1 + p_2 = 1$. The alternative hypothesis is $p_1 + p_2 > 1$.[28] Perfect market-timing ability gives $p_1 + p_2 = 2$. Henriksson (1984) used this test to investigate whether fund managers of 116 mutual funds exhibited positive forecasting ability over the period 1968–1980. For only four funds he was able to reject the null at 5 percent level. He found an average estimate for $(p_1 + p_2)$ of 0.984 with a standard deviation of 0.115.

TABLE A3—MARKET-TIMING ABILITY

Country	Correct Forecasts During May Through October: Bear Markets	Correct Forecasts During November Through April: Bull Markets	Total Number of Correct Forecasts (as Percentage)	Market-Timing Ability	p-Value
Australia	13	16	60.4	1.21	0.078
Austria	16	15	64.4	1.29	0.025
Belgium	16	20	75.0	1.50	0.010
Canada	14	16	62.5	1.25	0.045
Denmark	12	12	50.0	1.00	0.504
France	16	17	68.8	1.38	0.600
Germany	12	16	58.3	1.17	0.127
Hong Kong	12	17	60.4	1.21	0.078
Ireland	13	16	60.4	1.21	0.078
Italy	16	16	66.7	1.33	0.013
Japan	16	18	70.8	1.42	0.003
Netherlands	13	18	64.6	1.29	0.025
Singapore	18	13	64.6	1.29	0.025
South Africa	11	16	56.3	1.13	0.195
Switzerland	12	17	60.4	1.21	0.078
United Kingdom	13	18	64.6	1.29	0.025
United States	9	15	50.0	1.00	0.500
World index	14	15	60.4	1.21	0.078

Notes: Nonparametric test of predictability of the Halloween strategy over the years 1973–1996. Every year is divided into two parts: May through October and November through April. For the first period the Halloween strategy predicts a bear market (a return on the market lower than the risk-free rate). For the second period the Halloween strategy predicts a bull market (return higher than the risk-free rate). Total number of half-year periods equals 48.

On average, the Halloween strategy does well when judged on its ability to time bear and bull markets. The Halloween strategy appears to have better skills in forecasting bull markets than bear markets, because in most markets the values in the first column are lower than those in the second column. The score on the market-timing ability measure is above 1 or equal to 1 in all cases. In Belgium the strategy scores best, i.e., a market-timing ability of almost 1.50. When these values are compared with those of Table A1, we notice almost no differences. In general, when the annual outperformance of the Halloween strategy is high, so is its market-timing ability. Because we only examined 24 years of data, our sample size is quite small (i.e., $N = 48$). Nevertheless, the null hypothesis of no forecasting ability can still be rejected at a

[26] As we already know the potential source of superior performance, the Merton-Henriksson methodology is in our simple case similar to the methodology of Lawrence R. Glosten and Ravi Jagannathan (1994).

[27] Note that no assumptions about the structure of equilibrium security prices are required, because *ex ante* the investment manager's predictions are known.

[28] If the forecasts are known and forecasters behave rationally, then a one-tailed test as we use is most appropriate. Otherwise, a two-tailed test would be necessary. See Henriksson and Merton (1981).

FIGURE A2. END-OF-PERIOD WEALTH

Notes: End-of-period wealth for the two investment strategies over the period 1973–1996 in Italy.

90-percent significance level for 13 countries and for the World index.

While results reported here do not include transaction costs, they can easily be implemented. For instance, assuming conservative transaction costs of 0.5 percent for a single transaction,[29] the annual return on the Halloween strategy would drop approximately 1 percent.[30] For a practical implementation of the Halloween strategy, it would be more appropriate to mimic this strategy using index futures. In that case, transaction costs are much lower. For instance, Solnik (1993) estimates round-trip transaction costs of 0.1 percent on futures contracts.

Figure A2 shows the end-of-period wealth of an initial investment of one local currency unit during 24 years in Italy. Clearly, following a consistent Halloween strategy would have resulted in substantial higher wealth at the end of this 24-year period.

The results reported here reveal that a trading strategy of tactical asset allocation based on the old saying "Sell in May and go away" generates abnormal returns in comparison with stock market indices in most countries in our study. We find that this Halloween strategy (as it has been called by O'Higgins and Downes, 1990) beats a market index in every investigated country, except in Hong Kong and South Africa. This is surprising, as this outperformance is possible with a strategy that is less risky than simply holding the market index, measured by either standard deviation or beta. After correcting for risk, we show that this outperformance is statistically significant in many countries. The nonparametric test developed by Merton and Henriksson shows that the Halloween strategy is indeed very well able to predict half-year bull and bear markets. Again, these predictability results are statistically significant in many countries in our study. It therefore seems that stock returns can to some extent be predicted on the basis of their own past performance.

Some final considerations remain. One could argue that the Datastream market indices we use are not a proper benchmark and also that the Halloween strategy that invests half of the time in this index is therefore in practice an unobtainable investment strategy. The argument would be that is impossible to own a value-weighted country index with dividends reinvested, as the cost of continuously rebalancing this portfolio would be huge. The main reason to use indices with dividends reinvested is that the exclusion of dividends might, and in fact does, bias our results. This happens because in most countries dividend payments occur mainly during the May through October period. Excluding dividends would therefore bias the results in favor of the Halloween strategy. We also worked with market indices that do not correct for dividend payments (MSCI indices and the Citibase indices). The results based on these indices favored the Halloween strategy even more strongly.

While it is indeed difficult to mimic a value-weighted index in practice, there are several points to be made about this flaw in our analysis. Firstly, one could implement this trading

[29] One might argue that the costs of switching are in fact higher (two times 0.5 percent). However, we know of certain asset managers that charge transaction costs only once when an investor switches funds. Moreover, as noted by Glenn N. Pettengill and Bradford D. Jordan (1988): "certain families of mutual funds allow cost free switching from equity to money market funds."

[30] Stephen A. Berkowitz et al. (1988) estimate the cost of a transaction on the NYSE to be 0.23 percent. AEGON Asset Management estimates transaction costs for an institutional investor in the United States to be 0.21 percent, Europe 0.42 percent, and Japan 0.26 percent. These estimates, however, ignore tax and commission systems and market impact. Also bid/ask spreads are not constant but depend on the market environment.

strategy using index futures. This would also reduce transaction costs. Secondly, many countries in our study now have index-tracking funds, and the correlation between these index-tracking funds and the indices we use seems extremely high.[31] Thirdly, most of the indices we used are used in practice to measure the results of portfolio managers all around the world. Fourthly, most academic research uses value-weighted indices.

A more important problem with the implementation of this strategy may be the large size of the tracking errors in some years in comparison with the market indices. For institutional investors this might be a serious drawback for implementing a Halloween strategy because professional clients generally do not appreciate large tracking errors. In this case, a solution might be to use portfolio insurance during the May through October period. In a recent paper G. Waksman et al. (1997) show that in a situation where a market-timing strategy is not perfect, the use of portfolio insurance is optimal.

[31] Moreover, several institutions offer, occasionally tailor made, products that try to mimic a market in a specific countries. Examples of these products are the "Perles" introduced by NBS (Warburg).

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