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Seasonal Predictability of Stock Market Returns

by W. MARQUERING

Wessel Marquering
Erasmus University of Rotterdam,
Department of Finance, Rotterdam

ABSTRACT

This paper focuses on the seasonal predictability of stock market returns. We investigate the statistical significance of predicting stock returns from several calendar dummies. Our main findings, using monthly stock market returns from Belgium, Germany, the Netherlands, UK and US, are that the January effect disappears over time, but a strong support is found for the Sell-in-May effect. This implies that for each country, the returns are on average significantly higher in the winter than in the summer periods. Finally, we only find moderate support for a decennial cycle. Years ending in five have historically been the best years to invest in US stock, but this cycle effect is not found in the other countries.

> *"One of the earliest and most enduring questions of financial econometrics is whether financial asset prices are forecastable. Perhaps because of the obvious analogy between financial investments and games of chance, mathematical models of asset prices have an unusually rich history that predates virtually every other aspect of economic analysis. The fact that many prominent mathematicians and scientists have applied their considerable skills to forecasting financial securities prices is a testament to the fascinating and the challenges of this problem. Indeed, modern financial economics is firmly rooted in early attempts to "beat the market", an endeavor that is still of current interest, discussed and debated in journal articles, conferences, and at cocktail parties!"*
>
> *(Campbell, Lo and MacKinlay (1997) p.27)*

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I. INTRODUCTION

For many years, it was believed (especially under academics) that stock prices follow random walks, i.e. the best prediction of the next period's stock price is today's price plus a drift term. This would imply that stock returns are not predictable. There is growing evidence that stock market returns are predictable to some degree. The literature documents predictability of stock index returns from lagged returns, lagged financial and macroeconomic variables, and calendar dummies.

The guiding principle that asset markets are efficient and stock prices can be described by a random walk is simply stated, but its implications are many and subtle. The *Efficient Market Hypothesis* (EMH) has its roots in the pioneering work of Gibson (1889) who writes that "*when shares become publicly known in an open market, the value which they acquire may be regarded as the judgement of the best intelligence concerning them*", Gibson ((1889) p.11). It should be stressed that the views regarding the EMH are not the results from doctrinaire beliefs, but result from a large body of *empirical* work.[1] The EMH may be expressed in a number of alternative ways and the differences between these alternative representations can become rather entangled. The general idea behind the EMH is that asset prices are determined by the supply and demand in a competitive market with rational investors. These rational investors gather relevant information very rapidly and immediately incorporate this information into stock prices. If this information is immediately incorporated into prices, only new information, i.e. news, should cause change in prices. Since news is unpredictable by definition, price changes (returns) should be unpredictable. Contrary to most preceding research, Malkiel (1992) offers an explicit definition of the EMH:

> *"A capital market is said to be efficient if it fully and correctly reflects all relevant information in determining security prices. Formally, the market is said to be efficient with respect to some information set if security prices would be unaffected by revealing that information to all participants. Moreover, efficiency with respect to an information set implies that it is impossible to make economic profits by trading on the basis of that information set."*

To test the efficient market hypothesis, it is necessary to specify a model of "normal" expected returns. The classic assumption used to be that expected stock returns are constant over time, but there has been an increasingly amount of literature that provides evidence against this assumption. In particular, dividend yields and interest rates seem to have some significant predictive power. This phenomenon occurs over business cycle and longer horizons. Technical systems for predicting daily and weekly stock returns are still close to useless after transaction costs (see, e.g., Hawanini and Keim (1995)). While most financial economists seem to have accepted these views, they do not agree about the degree of the predictability.

Evidence of return predictability does not necessarily mean that markets are not (reasonably) efficient. Because of time-varying expected returns due to changing business conditions and risks, returns can be partly predictable, even when the EMH holds. Consequently, testing for efficient markets critically depends on the assumed model for the returns.

This paper presents an overview of the most important and latest empirical evidence in the predictability literature. Many recent studies report that the expected returns in stock markets are time varying and markets can be beaten by using calendar dummies or lagged financial and macroeconomic variables. The empirical part of this paper deals with the question whether stock returns are predictable from the following three seasonal patterns: the January effect, the Sell-in-May effect and the Years-ending-in-five effect. These anomalies would imply that the returns are on average higher in January, between November and April, and in years ending in five, respectively. This study aims to investigate these seasonalities in stock index returns of the stock markets of Belgium, Germany, the Netherlands, UK and US, over the period January 1973 – May 2002. This allows us to examine whether the seasonal patterns usually found in US data is also present in European data. In this paper we concentrate on lower frequency (monthly, yearly) seasonal patterns, as profitable exploitation of high-frequency seasonal patterns is reported to disappear when transaction costs are taken into account (see Lakonishok and Smidt (1988)).

The remainder of the paper is organized as follows. In Section II we present a review of the evidence on stock return predictability. Section III presents the statistical evidence of the January, Sell-in-May and Years-ending-in-five effects in Belgium, Germany, the Netherlands, UK and US. Section IV concludes and contains some final remarks.

II. REVIEW OF THE RETURN PREDICTABILITY LITERATURE

The literature on time-series return predictability[2] can be divided into three "branches": return predictability using lagged prices or returns, lagged financial and macroeconomic variables, and calendar dummies. The first branch of studies tries to predict stock returns using historical prices or returns. The central question in this branch of investigations is whether today's return is related to historical returns, at various frequencies. For example, Fama and French (1988) and Poterba and Summers (1988) study long horizon return predictability and find some evidence of mean reversion in returns over long-horizons (more than two years). In general, stock-index returns, or more generally returns of portfolios, tend to be positively (first-order) autocorrelated for most frequencies for most countries.[3] A possible explanation for this effect on daily or weekly data is nonsynchronous trading (see, e.g., Lo and MacKinlay (1990a,b) and Campbell, Lo and MacKinlay (1997), Chapter 2). In many cases this relationship is not statistically significant. Even if there is a significant relationship, it is typically too weak to obtain a higher return than the buy-and-hold strategy of the market portfolio after correction for risk and transaction costs. In other words, there is no *economic significance.*

Another example of the first branch of studies includes technical analysis. Technical analysis, also known as "charting", tries to forecast future returns from past prices. A majority of the financial economists used to be, and still is, very skeptical about this approach and its capability to generate abnormal returns. One of the main objections is the highly subjective nature of technical analysis. A recent paper by Lo, Mamaysky and Wang (2000), however, suggests that to some extent technical analysis can be useful out-of-sample and is able to generate abnormal returns even after correcting for transaction costs. Several popular technical indicators outperform passive strategies, using US stock market data from 1962 to 1996.

The second branch of studies examines the predictability using lagged economic and financial variables such as dividend yield and interest rates. Notable examples are the papers by Fama and French (1988), Breen, Glosten and Jagannathan (1989), Harvey (1991), Solnik (1993) and Pesaran and Timmermann ((1995), (2000)). For example, Pesaran and Timmermann (1995), using monthly US data from 1960 until 1992 and introducing model uncertainty, found statistically and economically significant return predictability using a variety of (lagged) explanatory variables. Among these are the dividend yield, the price-earnings ratio, the short interest rate, the long term bond return, the change in industrial production, and the twelve-month inflation rate. Solnik (1993), on the other hand, compares the predictability for Germany, France, the Netherlands, U.K., Switzerland, Japan, Canada and US, using the lagged dividend yield, a short term interest rate, a long term bond return.[4] Using monthly data from 1970 to 1990 he finds that especially the lagged dividend yield has a large predictive power for most countries.

Finally, the third branch of studies concentrates on the predictability by using seasonal (or calendar) dummies. If the simple notion of the efficient market hypothesis holds (i.e. prices follow a random walk), the expected return on a certain stock should be the same regardless of what day or month it is. Stated differently, the information of what day or month it is should have no predictive value for the price for the stock after this period. Evidence shows that this condition is not always true; therefore these seasonals are sometimes called anomalies.

A well-known[5] calendar effect is the *January effect*: index returns are on average higher in January than in other months (see, e.g., Rozeff and Kinney (1976) and Keim (1989)).[6] Hawanini and Keim (1995) show that the order of magnitude of this effect depends on the country and on the composition of the index. Because the January effect is especially present for small firms, the January effect is especially pronounced in equally weighted market indices. Nevertheless, the effect is usually also present in value-weighted indices. The most popular explanation for the existence of this effect is the tax-loss selling hypothesis (see, e.g. Bhabra, Dhillon and Ramirez (1996)). This hypothesis states that there is a heavy selling pressure at the end of the tax year, since in some countries the sale of securities that have experienced price declines, i.e. capital losses, can be offset against taxable income. Small stocks are more likely to be used for this as they are riskier in general, so that they have a higher probability of large price declines. In the beginning of the new tax year investors typically reinvest in these (or similar) stocks, leading to a relative high return in January. An alternative explanation is "window dressing": investment managers might sell "loser" securities at the end of the year to present a nice portfolio at the beginning of the year (see Haugen and Lakonishok (1988)).

Another seasonal effect includes the *day-of-the-week effect*, which refers to the finding that Monday is a relatively bad day, while Friday is a relatively good day for stock prices (see, e.g., French (1980), Keim and Stambaugh (1984), and Hawanini and Keim (1995)). Chang, Pinegar and Ravichandran (1998) show that the day-of-the-week effect weakens substantially when responses to macroeconomic news are taken into account. The response of smaller stocks to this kind of news is typically high on Mondays, especially in down markets. Similar to the day-of-the-week effect, literature shows that there is a *turn-of-the-month effect*. For example, Ariel (1987) and Cadsby and Ratner (1992) show that returns are on average higher on the last day of the month and the first day of the next month.[7] The well-documented *holiday effect* (see, e.g., Lakonishok and Smidt (1988) and Ariel (1990)) implies that prices rise on average more on the day(s) proceeding holidays. This effect is not only present in US stock markets, but holds more universally. Cadsby and Ratner (1992) and Kim and Park (1994) show that the holiday effect is present in international stock markets. Typically, the holiday effect is only present for the *local* holiday. Due to transaction costs it is, in general, not profitable to trade on the basis of these anomalies.

A recent study uncovers that a strategy based on another seasonal effect, namely the *Sell-in-May effect*, remains surprisingly profitable for many countries in case of reasonable transaction costs (Bouman and Jacobsen (1999)). This strategy, which is based on the old (English) stock market wisdom "*Sell in May and go away, but remember to come back in September*", advises investors to sell their stocks in May and buy again in September. A closely related strategy is the Halloween indicator, so named (in the US) because it would have you in the stock market from October 31 to April 30 and out of the market for the other half of the year (see O'Higgins and Downes (1992)). The Belgian version of the wisdom tells us to sell around Brussels Fair (early June) and buy around Leuven Fair (September). Bouman and Jacobsen (1999) suggest that this anomaly is related to the duration of summer holiday in the particular country. The longer the holiday, the larger the difference between the returns in winter (from November until April) and summer (from May until October) months.

Another strong, but not so well known seasonal pattern is the *Years-ending-in-five effect*. This decennial cycle, originally identified by Edgar Lawrence Smith in his book "Common Stocks and Business Cycles", was documented in 1924. Smith found that years ending in 7 have the worst returns, while years ending in five have by far the best returns on average. Since the 1880s, the US stock market has never had a down year in any year ending in five. The decennial cycle holds up well although Smith could never explain it. Of course, decennial cycles may be purely random events.

For all of the three branches above, we should be aware of the danger of *data snooping*. If you try a great number of different variables to predict stock returns, you will eventually find some variables that have statistically significant predictive power, so apparently there is a genuine relationship. Thus, because so many variables have been tried, it is not surprising that one eventually finds variables with forecasting power.[8] The danger is that it works well within the sample, but will have no predictive power out-of-sample. Because many researchers use the same data sets (particularly for the US) this data-snooping problem carries over to other studies. To circumvent this problem we can study data sets of other countries[9] and more recent samples. Lo and MacKinlay (1990b) study this problem technically by specifying a-priori data-snooping strategies. They conclude that in general the amount of forecastability found empirically (for various strategies) is larger than what can be explained by data snooping only. For technical trading rules (used by, e.g., technical analysts), however, Sullivan, Timmermann and White (1999) find that there is no evidence of outperformance anymore once data-snooping effects are taken into account. A phenomenon which is possibly related to the data snooping is the empirical finding by Dimson and Marsh (1999), that many anomalies disappear or reverse itself after they are published, which they refer to as (an application of) Murphy's law. Next section examines the predictable seasonal patterns in monthly returns. We examine whether the January effect, Sell-in-May effect and Years-ending-in-five effect is present in Belgium, Germany, the Netherlands, UK and US.

III. SEASONALITY IN STOCK MARKET RETURNS

To examine the January effect, Sell-in-May effect and Years-ending-in-five effect, we use data on the monthly stock returns of the following value-weighted market indices: BEL 20 (Belgium), DAX 100 (Germany), AEX (the Netherlands), FTSE 100 (UK), and S&P 500 (US). All series are Datastream re-investment indices[10] (expressed in local currencies) over January 1973 – May 2002, except the S&P 500 index, which starts in January 1965. In Table 1 we report some summary statistics of the indices over the entire period and the anomaly period corresponding to the January effect, the Sell-in-May effect and the Years-ending-in-five effect. To examine the Sell-in-May effect, we follow Bouman and Jacobsen (1999) and divide the sample into "winter" (November through April) and "summer" (May through October) periods. The results in Table 1 show that for each country the returns are relatively high on January, in winter periods and in years ending in five. Higher returns during the outperforming period could just be a compensation for higher risk in these periods. As can be seen from Table 1, risk, measured by the standard deviation, tends to be similar in all periods. This suggests that the seasonal effects are not just a compensation for higher risk. Figures 1 – 3 display graphical illustrations of the average monthly return in the anomaly period and the average return during the other months. The monthly returns are simple percentages.

First we examine the well-known anomaly that stocks have historically generated abnormally high returns during the month of January.

TABEL 1

SUMMARY RESULTS

Summary results on value weighted re-investment indices for Belgium, Germany, the Netherlands, UK and US.

	All Months	January	Winter	Years in 5
Belgium				
Mean (%)	0.881	2.439	1.656	1.787
Std. Dev. (%)	5.148	6.096	5.293	5.080
Germany				
Mean (%)	0.809	1.354	1.493	2.848
Std. Dev. (%)	5.475	4.633	4.850	5.685
Netherlands				
Mean (%)	1.087	2.884	1.942	2.199
Std. Dev. (%)	5.028	5.947	4.846	4.933
UK				
Mean (%)	0.951	2.348	1.723	1.395
Std. Dev. (%)	4.764	4.743	4.225	3.079
US				
Mean (%)	0.665	1.712	1.121	1.923
Std. Dev. (%)	4.366	5.152	4.155	3.382

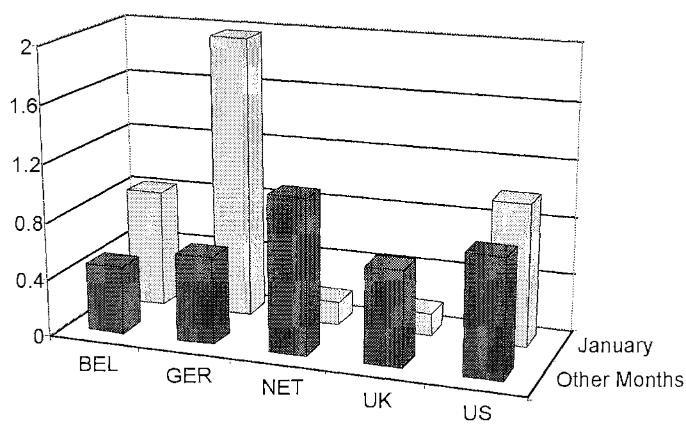
Table 1 and Figure 1 indicate that there is an overwhelming January effect for all five countries. The January effect seems largest for the Belgium, the Netherlands and the UK. A natural question to ask is whether this anomaly is statistically significant. To examine whether strategies based on this January effect have significant forecasting power, we use the following equation:[11] [12]

$$R_{t+1} = \alpha_0 + \alpha_1 \mathrm{Jan}_{t+1} + \varepsilon_{t+1}, \tag{1}$$

where Jan_t is a dummy for the month January: 1 for observations relating to the month January, and 0 for observations from the other months. We test whether the coefficient of Jan_{t+1} is significantly different from zero. When α_1 is positive and significant, we reject the null hypothesis of no January effect. In that case the mean returns in January are on average significantly higher than other months. When α_1 in (1) is zero, we obtain the random walk model. In Panel A of Table 2 we report some basic estimation results of equation (2). The table shows that the January effect is statistically significant in two out of the five countries at the five percent significance level (a t-value greater than 1.96). The fact that we do not observe a January effect in the UK could be due to the fact that the UK does not use December 31 as the tax year-end. Given Figure 1 and previous studies, it is quite a surprise that we only find a significant effect in two out of the five countries. As anomalies could disappear as many traders

FIGURE 1

Average returns in January and February-December



attempt to take advantage of it in advance, it is well possible that the January effect disappeared in recent years. To investigate this question, we look at a more recent period, namely January 1990 through May 2002 below. But first we consider another striking seasonal effect; the one based on the old market wisdom: "Sell in May and go away, but remember to come back in September".

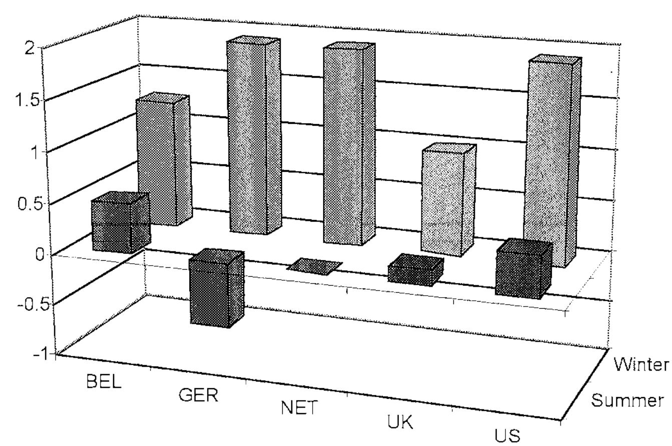
Looking at Figure 2, we see that the average returns differ much between summer and winter periods. Returns over the May-October period tend to be close to zero in all countries. For Belgium, Germany and the Netherlands, the average return in the summer period is even negative. Like Bouman and Jacobsen (1999), we also find that the difference is smallest for the US. As indicated in Section II, this could be related to the relatively short period of summer holiday in the US. To examine if strategies based on the Sell-in-May effect have significant forecasting power for monthly returns, we use the following model:

$$R_{t+1} = \beta_0 + \beta_1 S_{t+1} + \varepsilon_{t+1}, \tag{2}$$

where S_t is the "Sell-in-May indicator": 1 for observations from the months November through April, and 0 for observations from the other

FIGURE 2

Average returns in May-October ("Summer") and November-April ("Winter")



TABEL 2
SEASONAL EFFECTS

*Results of estimating equations (1)-(3) using the returns on the value weighted stock indices for Belgium, Germany, the Netherlands, UK and US. The t-values based on heteroscedasticity consistent standard errors are reported in parentheses; * indicates that the corresponding coefficient is statistically different from zero at the five percent significance level.*

Explanatory Variables	*Belgium*	Germany	*Netherlands*	UK	US
Panel A: January Effect					
Constant	0.005	0.006*	0.007*	0.008*	0.006*
	(1.781)	(2.154)	(2.415)	(2.843)	(2.627)
Jan_{t+1}	0.019*	0.007	0.022*	0.015	0.011
	(1.966)	(0.680)	(2.234)	(1.503)	(1.554)
R^2	0.011	0.001	0.014	0.008	0.005
Adj. R^2	0.008	−0.002	0.011	0.004	0.003
Panel B: Sell-in-May Effect					
Constant	−0.003	−0.001	−0.002	0.002	0.002
	(−0.960)	(−0.218)	(−0.579)	(0.393)	(0.647)
S_{t+1}	0.020*	0.016*	0.022*	0.016*	0.009*
	(3.744)	(2.794)	(4.064)	(2.817)	(2.254)
R^2	0.038	0.022	0.045	0.027	0.011
Adj. R^2	0.036	0.019	0.042	0.023	0.009
Panel C: Years-Ending-in-Five Effect					
Constant	0.005	0.005	0.007*	0.009*	0.005*
	(1.864)	(1.539)	(2.471)	(3.046)	(2.298)
$Y5_{t+1}$	0.013	0.024*	0.015	0.005	0.014*
	(1.414)	(2.430)	(1.723)	(0.706)	(2.652)
R^2	0.006	0.018	0.008	0.001	0.010
Adj. R^2	0.003	0.015	0.005	−0.003	0.008

months.[13] We reject the null hypothesis of no Sell-in-May effect when β is positive and significant.

Panel B of Table 2 shows that in each country there is a statistically significant Sell-in-May effect present at the five percent level (t-value larger than 1.96). The effect is highly statistically significant as all t-values are considerably greater than 1.96.[14] The t-value found in the US data is somewhat higher than the corresponding one in Bouman and Jacobsen (1999). Using data from January 1970 to August 1998 they find a t-value of 1.95. A possible reason that the Sell-in-May effect is weakest in the US is possibly related to the length of summer holidays, which is shorter in the US than in the four European countries.

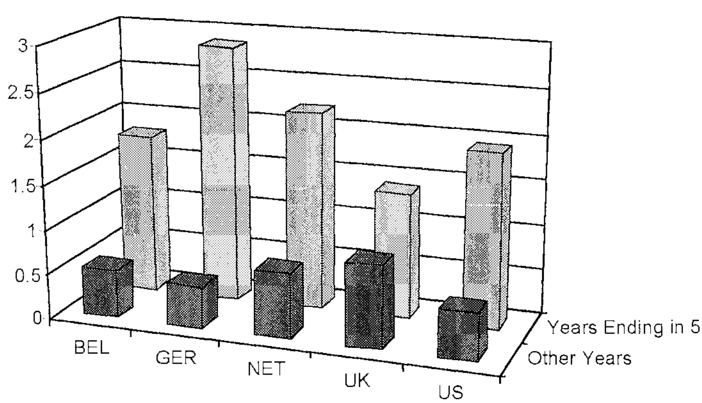
The third seasonal effect that we consider more thoroughly is the Years-ending-in-five effect. Smith (1924) documented in the early 1920s that years ending in five have by far the best returns on average.[15] The literature has been remarkably silent about this phenomenon. Table 1 shows that for the five countries the average returns in years ending in five is substantially greater than the average return over the entire period. Figure 3 displays the average monthly returns in years ending in five and in years ending in other numbers. Again, for all countries (except for the UK) the differences between the two periods are substantial. For Germany, for example, the average returns are more than two percent higher in years ending in five than years ending in other numbers. To test if years ending in five have a significant higher average return than other years, we use the following equation:

$$R_{t+1} = \gamma_0 + \gamma_1 Y5_{t+1} + \varepsilon_{t+1}, \quad (3)$$

where $Y5_t$ is an indicator for a year ending in five: it takes the value 1 for the observations in the years ending in five, and 0 for the other

FIGURE 3

Average returns in years ending in five and other years



observations. Panel C of Table 2 shows that the Years-ending-in-five effect is only statistically significant for Germany and the US. While Figure 3 suggests that the decennial cycle is also present in Belgian, Dutch and UK returns, it is not statistically significant.

The next step is to look at the recent period January 1990 – May 2002. The reason for this is twofold. First, if the apparent anomaly is a result of data snooping, it should disappear in later data. The second reason to look at recent data is that theoretically, in markets without frictions, an anomaly should disappear as traders attempt to take advantage of it in advance. Figures 4 through 6 display the average monthly returns in the anomaly period and the averages in other months for the period January 1990 – May 2002. Figure 4 suggests that the January effect largely disappeared over the last decade. In the Netherlands and UK, for example, the January effect even seemed to have reversed itself, while the January effect remains substantial in Germany. If the January effect would be a profitable anomaly to base a strategy on, it should be there for all countries and for all (recent) periods. To check the statistical significance of this anomaly, we run regression (1) over the period January 1990 – May 2002. Panel A of Table 3 shows that the coefficient of the January dummy is not significantly different from zero anymore for any country. Thus, the January effect seemed to have disappeared in value weighted stock market indices. Some[16] believe the January effect has moved into November and December as a result of

FIGURE 4

Average returns in January and February-December, 1990-2002

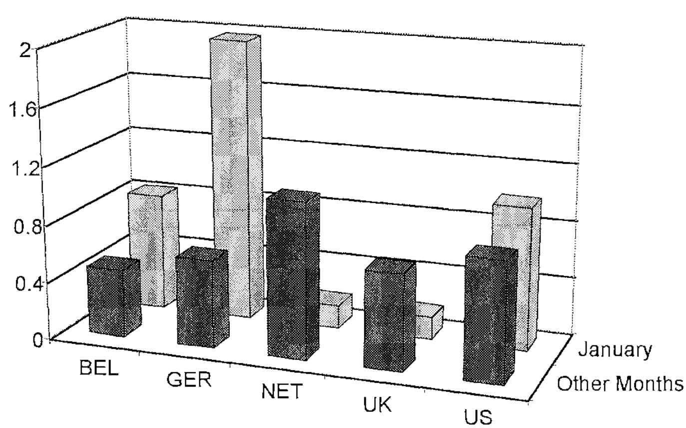


TABLE 3

SEASONAL EFFECTS: THE PERIOD 1990-2002

*Results of estimating equations (1)-(3) for the period 1990:1 – 2002:5, using the returns on the value weighted stock indices for Belgium, Germany, the Netherlands, UK and US. The t-values based on heteroscedasticity consistent standard errors are reported in parentheses; * indicates that the corresponding coefficient is statistically different from zero at the five percent significance level*

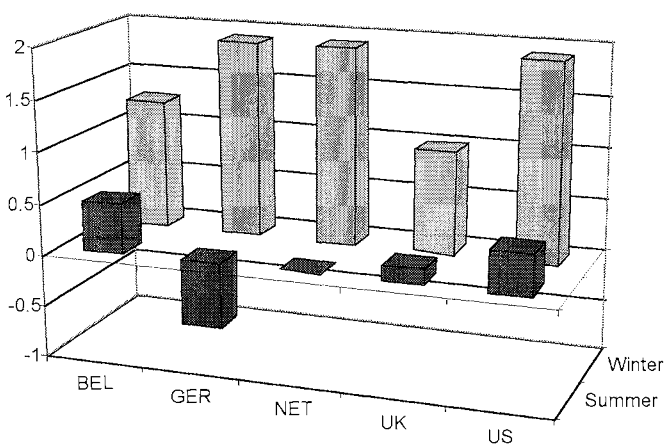
Explanatory Variables	*Belgium*	Germany	*Netherlands*	UK	US
Panel A: January Effect					
Constant	0.005	0.005	0.011*	0.006	0.008*
	(1.267)	(1.067)	(2.577)	(1.748)	(2.247)
Jan_{t+1}	0.003	0.014	−0.009	−0.005	0.002
	(0.193)	(1.167)	(−0.707)	(−0.413)	(0.167)
R^2	0.000	0.005	0.003	0.001	0.000
Adj. R^2	−0.006	−0.002	−0.004	−0.006	−0.007
Panel B: December Effect					
Constant	0.003	0.005	0.008	0.004	0.007
	0.721	0.948	1.957	1.155	1.886
Dec_{t+1}	0.028*	0.024	0.022*	0.021*	0.019
	2.718	1.608	2.054	2.539	1.818
R^2	0.027	0.013	0.016	0.019	0.015
Adj. R^2	0.021	0.006	0.009	0.013	0.008
Panel C: Sell-in-May Effect					
Constant	−0.003	−0.006	0.000	0.002	0.004
	−0.525	−0.861	0.004	0.293	0.807
S_{t+1}	0.015*	0.025*	0.019*	0.008	0.009
	2.053	2.747	2.506	1.252	1.246
R^2	0.028	0.049	0.041	0.011	0110
Adj. R^2	0.021	0.043	0.035	0.004	0.004
Panel D: Years-Ending-in-Five Effect					
Constant	0.005	0.007	0.009*	0.005	0.007
	1.151	1.320	2.283	1.364	1.860
$Y5_{t+1}$	0.006	−0.000	0.003	0.011	0.018*
	0.574	−0.013	0.371	1.577	3.254
R^2	0.001	0.000	0.000	0.005	0.014
Adj. R^2	−0.006	−0.007	−0.006	−0.002	0.007

mutual funds being required to report holdings at the end of October and from investors buying in anticipation of gains in January. To examine this question, we run a regression with a December dummy instead of the January dummy. Panel B of Table 3 shows that for Belgium, the Netherlands and UK, we find a significant December effect for the period 1990:1-2002:5. This supports the hypothesis that the January effect has moved into December. We also ran a similar regression with a November dummy. Contrary to Bhabra, Dhillon and Ramirez (1996), our results (not reported) strongly reject the presence of a November effect in each country.[17]

Looking at Figure 5, we see that the Sell-in-May effect seems to remain in the recent sample for each country, suggesting that this anomaly has not disappeared over time. The "Sell-in-May results", presented in Panel C of Table 3, show that the anomaly is still statistically significant for Belgium, Germany and the Netherlands. This Halloween strategy also yields excess returns for the UK and US, but these are not statistically significant anymore. Note however that the power of the significance test is reduced as we have fewer observations in the recent sample. To test the possibility that the Sell-in-May effect is simply the January effect in disguise, we consider a regression in which we additionally include a January dummy.

FIGURE 5

Average returns in May-October ("Summer") and November-April ("Winter"), 1990-2002



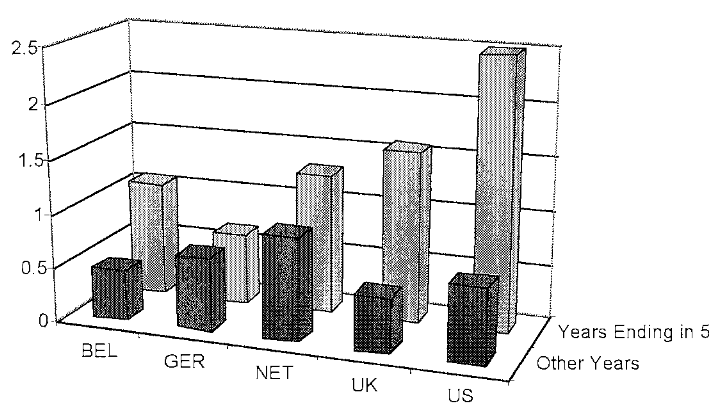
This resulted in quantitatively identical results: a statistically significant Sell-in-May effect for Belgium, Germany and the Netherlands.

Finally, Figure 6 suggests that the Years-ending-in-five effect largely disappeared over the last decade. Only for the UK and US there seems to remain a decennial cycle. Panel D of Table 3 provides statistical evidence that the Years-ending-in-five effect is only significant for the US over the period 1990:1 – 2002:5. It is important to realize that the t-tests are not fully reliable, given the number of observations in this sample. Because the Years-ending-in-five effect is a long-term cycle, we need many years of data to draw statistically reliable conclusions concerning the decennium effect.[18] Despite this limitation we can conclude that overall we find only very little support of this possible decennial cycle outside the US. Consequently, it is well possible that this seasonal effect is just a random event.

Whereas the January effect and Years-ending-in-five effect seem to have disappeared over time, the Sell-in-May effect is still present. Moreover, it is not unlikely that this effect will continue to exist. Data snooping seems an unlikely explanation for the Sell-in-May anomaly. Unlike the January effect and Years-ending-in-five effect, the Sell-in-May strategy is not selected from a large universe of calendar rules, as the strategy is based on an old market wisdom. While there are some possible explanations for the January effect, we do not find any outperformance in January anymore using the recent data. If there really is a January effect, it should have showed up in the recent data

FIGURE 6

Average returns in years ending in five and other years, 1990-2002



as well. Instead it disappeared. The effect seems to have shifted to December. As the Years-ending-in-five effect is found by trying many possible calendar anomalies, it is almost surely to disappear in the future. While the difference in returns for the period 1973 – 2002 look impressive, only for Germany and the US there is a statistical outperformance for years ending in five. Moreover, the outperformance of 1995 – the most recent year ending in five – is less spectacular and only statistically significant for the US.

IV. CONCLUSIONS

Recent literature seems to suggest that stock returns are predictable to some degree. Seasonalities in stock market returns, for example, are documented extensively. In the empirical application of this paper we investigated the statistical significance of predicting stock returns from several calendar dummies. The data includes the monthly indices from Belgium, Germany, the Netherlands, UK and US. Our main findings indicate that the Sell-in-May effect is clearly present in each country. The returns in winter months (from November until April) are much larger than those in summer months (from May until October) months. The finding of a relatively strong effect for European countries seems to be consistent with the relatively long summer holiday in European countries. The Sell-in-May effect is still present in recent data and it is not unlikely that this effect will continue to exist.

January has historically been the best month to be invested in stocks. However, only for Belgium and the Netherlands we find a significant January effect between January 1973 and May 2002. Over the recent period, January 1990 – May 2002, the anomaly is not present anymore and for some countries the January effect seemed to have reversed itself. This suggests that the anomaly disappeared because traders took advantage of it in advance. There now seems to be a December effect, which is possibly an anticipation effect.

Another remarkable, but not so well known seasonal pattern is the Years-ending-in-five effect. The US stock market has never had a down year in any year ending in five. Our results suggest that there only is a statistically significant effect for Germany and the US. As the Years-ending-in-five effect is selected from a wide universe of calendar rules and is mainly present in the US, it is likely that this decennial cycle is purely a random event.

NOTES

1. One of the earliest empirical study includes Cowles (1933).
2. Note that we only focus on the time-series predictability of returns. For an overview of cross-sectional return predictability see, e.g., Hawanini and Keim (1995).
3. Individual stock returns, on the other hand, tend to be negatively autocorrelated on a daily and weekly frequency, possibly due to overreaction effects and market microstructure effects (see Campbell, Lo and MacKinlay (1997), Chapter 2, and Jacobsen (1999)). While the relation is statistically significant in many cases, most of the predictability using past returns disappears when (information and) transaction costs are taken into account, especially the predictability found on high-frequency basis. The fact that individual securities are weakly negatively autocorrelated, while portfolio returns, which are essentially averages of individual security returns, are strongly positively autocorrelated looks somewhat paradoxical at first sight, but this effect is due to large positive cross-autocorrelations across individual securities across time (see Campbell, Lo and MacKinlay (1997), Chapter 2).
4. Moreover Solnik (1993) uses a January dummy to account for the possible January effect as described above.
5. "The January effect is perhaps the best-known example of anomalous behavior in security markets throughout the world", Haugen and Jorion (1996).
6. Bhabra, Dhillon and Ramirez (1996) document the existence of a November effect in US stock returns.
7. In a related paper, Wang, Li and Erickson (1997) show that the day-of-the-week effect occurs primarily in the last two weeks of the month. They find that this phenomenon cannot fully be explained by the turn-of-the-month effect.
8. For example, Krueger and Kennedy (1990) show that if the winning team of the American Super Bowl (which is held in January) is a team from the National Football League (rather than from the alternative American Football League), the US stock market will most probably rise that year. This indicator predicts the stock market direction more than 90% of the years correctly between 1967 and 1988!
9. Because most international stock markets returns are highly correlated with the U.S. stock market returns, it is still likely that these datasets still suffer from the data snooping problems.
10. This means that all dividends are re-invested in the indices.
11. Including a lagged return on the market portfolio to correct for possible autocorrelation in returns does not yield to qualitatively different results for all regressions. Monthly returns exhibit no significant autocorrelation.
12. For simplicity, we denote in all models the error term as ε_t in this paper, although they do not represent the same.
13. We obtain very similar results when the indicator is equal to 1 in October as well.
14. Although we (statistically) reject the random walk model and find predictability in returns, one should be careful in interpreting these results. Rejecting the random walk model, does not necessarily imply that we can profit from this predictability in practice. Rather than looking only at the statistical significance we should also examine the economic significance of the predictability. In other words, can we exploit this predictability out-of-sample and after correcting for risk considerations and transaction costs? Marquering and Verbeek (2001) show how to measure the economic significance, by examining predictability using financial and macroeconomic variables. They find that strategies based on this predictability is economically significant, but deteriorates after 1990.
15. Whereas Smith (1924) found that years ending in seven have the worst returns, we do not find any significant abnormal return for years ending in seven for all countries. The results can be obtained from the author upon request.

16. See, e.g., Bhabra, Dhillon and Ramirez (1996).
17. The results can be obtained from the author upon request.
18. Alternatively, we could test whether the statistical evidence of a decennium effect in the US is due to 1995. This hypothesis is tested using samples 1965:1-1990:12 and 1954:1-1990:12. The results (not reported) show that the Years-ending-in-five effect in the US is not due to 1995.

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