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A PROMISING TIMING STRATEGY IN EQUITY MARKETS

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Abstract: In a working paper, Jacobsen and Bouman (2001) claim that that the old stock market saying of "sell in May and go away but buy back by St. Leger Day" produces statistically significant profit when tested on a large database of equity market returns over the last decade, three decades, and even longer periods. In a recently published paper, Sullivan, Timmerman and White (2001) dismissed the statistical significance of this or any other calendar-based trading rule, attributing the reported test results to a large data mining exercise of the academic and financial communities. In this paper, we provide an out-of-sample test on the Bouman and Jacobsen strategy and conclude that the reported results are indeed statistically significant. In doing so we reintroduce a reliable index of capital returns on the Irish equity market maintained contemporaneously by the Irish Central Statistical Office (and its forerunner) since January 1934 which, in its early decades, displays markedly different statistical properties to both the US and UK equity markets of that time and equity market returns generally in recent decades. As a subsidiary exercise we reconsider the extensive literature on monthly seasonality in equity markets with this novel index. It is contended that the abnormally high returns frequently reported in January and April and occasionally in February and other months are perhaps more accurately and certainly more parsimoniously ascribed to the half-year effect captured in the old stock market adage.

Keywords: Irish equity market; monthly seasonalities; January effect; data mining; trading strategy.
JEL Classifications: N24, G15, C32.

1. INTRODUCTION

The Holy Grail of investors is to find a strategy that produces excess returns without incurring extra risk. Like the Holy Grail, the existence of such a strategy has previously been denied, with early statistical evaluation of putative rule-based trading strategies or expert-devised strategies not demonstrating added value. Landmarks in this literature are Cowles (1933), Cowles and Jones (1937), Cowles (1944) and Kendall (1953). These empirical findings, coupled with the theoretical insight of Samuelson (1965), lead to the formulation of initially the random walk hypothesis in Fama (1965) and later to the more general Efficient Market Hypothesis (EMH) in Fama (1970).[1] Both of these hypotheses dismiss the possibility of systematically achieving risk-adjusted excess returns from stock markets.

During the 1980s there was a retreat from the previous, almost dogmatic, acceptance of the EMH. Now academics have joined market professionals in the search for unusually profitable investment strategies and the *Journal of Finance*, which was the original outlet for Fama's exposition of the EMH, entertains articles purporting to demonstrate exploitable market opportunities (or "anomalies" as they are often called). In recent times, for instance, Lo, Mamayasky and Wang (2000) claim to demonstrate that certain stock price patterns that long excited technical analysts, such as head-and-shoulders and double-bottoms, do "*provide incremental information and may have some practical value*". Indeed, one of the authors of this later paper is confident that at least some technical trading rules will prove abnormally rewarding[2] and now manages a fund of half a billion dollars to see if he is right.[3] Lo *et al*. is just one in a clutch of research that directly challenge Kendall's conclusions and with it the EMH in its weakest form. Another strand in the recent literature is to review Cowles' famous conclusion of "It is doubtful" to the title question of his 1933 paper "Can Stock Market Forecasters Forecast?". Brown, Goetzmann and Kumar (1998), for instance, review some of Cowles' evidence with modern statistical methods and come to the opposite conclusion.

Perhaps the most striking claim of an unusually profitable trading strategy, at least as far as the average equity investor is concerned, is made in a forthcoming paper by Jacobsen and Bouman (2001). They claim that they have discovered a simple strategy that will outperform the stock market while, at the same time, halving the risk. It works in 36 out the 37 equity markets analysed; it works in large established markets such as the US and in small emerging markets such as Indonesia; it works over the last decade and the last three decades; it works after full allowance for trading expenses and taxes; it works out-of-sample as far back as they could find data – for instance, in Japan since 1920, in France since 1900, in the US since 1802 and in the UK market since 1694. It works in Ireland and it works especially well in Europe. The excess risk-adjusted profit of their proposed strategy is demonstrated to be not just economically significant but also statistically significant.

The trading rule leading to the extraordinary claim will be recognised by anyone who ever served an apprenticeship in the markets. "Sell in May and go away but buy back by St. Leger Day" is one of the nursery rhymes of the stock market of uncertain origin. St. Leger is the oldest classic horse race in the world, run since 1776 at Doncaster (so-called since 1778) so the saying could be of very old vintage.[4] This adage encapsulates the simple trading rule: sell on 1 May but buy back into the market in autumn sometime. Bouman and Jacobsen show that it matters little whether one buys back in September or October, and adapt the rule so that one buys back at Halloween. The resulting rule is then simply to be in cash for half the year

(May to October) and in the equity market for the other half (November to April). The positive returns delivered by stock markets, it is contended, tend to be concentrated in the November-April six months of the year, with the other half of the year delivering poor, often negative, returns.

In the first section of this paper we review the paper by Bouman and Jacobsen that makes the claim. We contend that, striking as their finding is, it might be the result of data mining, as is contended in Sullivan, Timmerman and White (2001). To settle the dispute we go on to bench test their trading strategy against a heretofore unstudied data source – the Irish equity market in its earlier days.

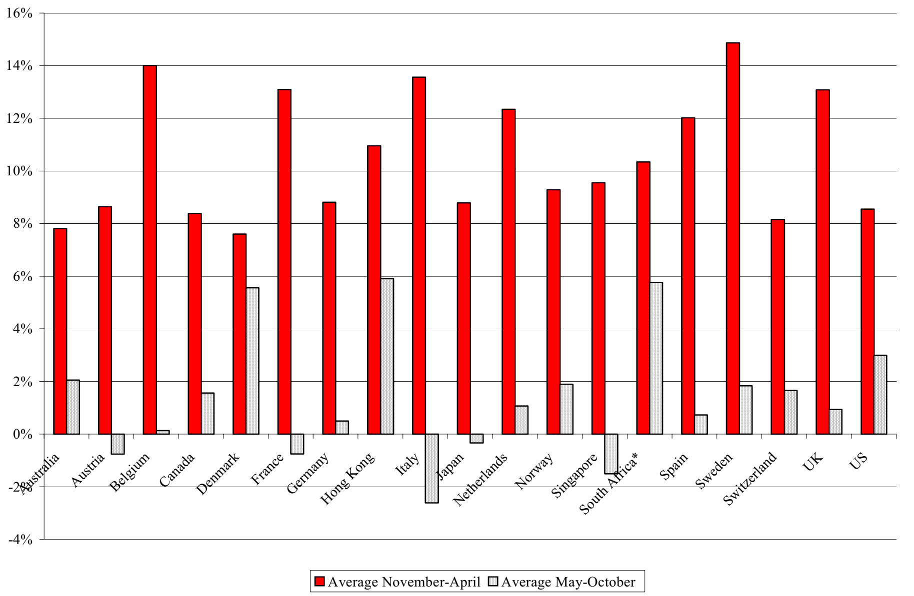
The Irish Stock Exchange is one of the oldest in the world, dating from the end of the eighteenth century. It has an unusually good set of records, ranking it amongst the best for historical research. In particular, the *CSO Price Index of Ordinary Stocks and Shares of Companies incorporated in Ireland (except Railways)* is a monthly capitalised weighted arithmetic index with almost complete coverage of the Irish stock market, which dates from January 1934. This modern method of construction was superior to many of the indices at that time, such as the Dow Jones Industrial Average (probably the first stock index, dating from 1884) and the UK FT Ordinary Index. The CSO Index gives us a reliable barometer of the Irish equity market – more reliable than other researchers must make do with on their own markets. Further, ledgers deposited at the National Archives of Ireland chronicle the price of every transaction every day of every year from 1802 to 1879 on the Dublin Stock Exchange. This unique record, extending to before limited liability was common, is a treasure-trove for the financial researcher. In fact, we need tap into just a mere fraction of this extraordinary database to provide an independent test of the trading rule. We extensively exploit the CSO Price Index, show that is quite distinct from the stock indices analysed by Bouman and Jacobsen, thus providing us with a valuable out-of-sample test for their findings.

2. "SELL IN MAY AND GO AWAY BUT BUY BACK BY ST. LEGER DAY"

It is remarkable that the profitability or otherwise of the above aphorism in the markets has not been systematically studied until recently. Perhaps the lure of the novel and the sophisticated has seduced researchers into more complicated ways of trying to beat the market. But, say Jacobsen and Bouman (2001), trading on the old wives' tale is considerably better than most such complicated schemes. Simply, sell in May, hold cash until (in a slight change to simplify the old rule) the end of October, and then buy back into the equity market. The markets, they contend, deliver poor returns through the summer and autumn months, with all the positive returns coming through in winter and spring.

This assertion is easily tested. We need just breakdown the annual returns of equity markets into these two half years and look at the results. Figure 1 does just this for 19 of the largest equity markets in the world over the last three odd decades.

Figure 1: Average returns over two 6 month periods, major markets: January 1970 to August 1998

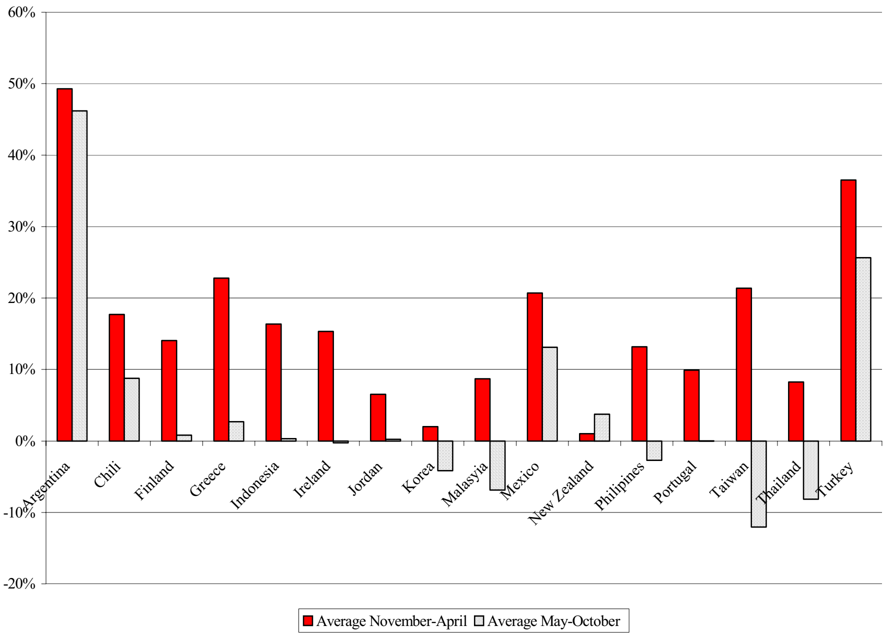


Source: MSCI Indices with dividends reinvested, local currency.
From Bouman and Jacobsen (2001), with data kindly provided by them.
*Returns for South Africa date from 1973.

The graph shows that in every one of the nineteen major markets studied over the last 30 odd years, the greater part of the return for the year is concentrated in the November to April period. The effect is very pronounced, with the (unweighted) average for the 19 markets being 10.5 per cent in November to April and just 1.4 per cent in the May to October period. The effect cannot be accounted for by a seasonal incidence of risk as Bouman and Jacobsen demonstrate that risk, under the usual definition of standard deviation of returns, is similar in both halves of the year. It seems that the equity risk premium – that is, the compensation for holding risky equities as opposed to the safer investments such as cash – is paid in just six months of the year.

The nineteen markets above capture 97 per cent of the total market capitalisation of world equity markets at the present time. MSCI indices with dividends reinvested are available for many smaller markets from 1988 and these are graphed overleaf for a further sixteen markets.

Figure 2: Average returns over two 6 month periods, minor markets: January 1988 to August 1998



Source: MSCI Indices with dividends reinvested, local currency.
From Bouman and Jacobsen (2001), with data kindly provided by them.

The seasonal pattern is evident again in the sixteen minor markets, including that of Ireland, over the last decade. We note that it does not work in just one country, New Zealand, where the half-year ending April outperforms the other half-year by an average of 2.7 per cent per annum. The unweighted average of the returns over the sixteen markets is 16.5 per cent between November and April and 4.2 per cent between May and October. Excluding the high performing markets of Argentina and Turkey, the fourteen-market average is 12.7 per cent versus – 0.3 per cent.

In summary then, the trading rule works with economic significance in thirty-four of the thirty-five markets.[5] By selling in May and buying back six months later one avoids the unrewarding gyrations of the markets. Naturally these results are statistically significant, with the authors reporting significance at the 1 per cent level for ten countries and at the 10 per cent level for twenty countries.

Finally, if in need of more convincing, Bouman and Jacobsen perform a test of their theory by applying it to a database of historic market returns. They trace returns on eleven markets back as far as records allow and assess how their rule would have worked up to December 1969. They report that it was profitable on a risk-adjusted basis in ten out of the eleven markets (failing in Australia) and was statistically significant at the 10 per cent level in the UK market since 1694 and at the 5 per cent level in the Japanese market since 1920, the Canadian market since 1933, and the Dutch market since 1950.

3. THE CHARGE OF DATA MINING

The most compelling part of the previous argument is that it works on so many markets over the last few decades and on several other markets over longer periods. If, however, all markets were reasonably integrated over the period analysed, so that movements in one market were highly dependent on another, then the numerical weight of the evidence gained from the different markets is considerably reduced. National capital markets have been shedding their distinctiveness over the last few decades with the progressive liberation of controls on capital flows. So, perhaps in recent decades we are merely identifying the same global equity pattern in its many manifestations, not different instances of the same pattern. Second, as O'Rourke and Williamson (1999) show in their survey, international capital markets were also extremely well integrated in the late nineteenth century, so even the long term market returns might not be capturing fundamentally different data sets. These doubts – and they are only that – make us rely more on the statistical evidence presented: the pattern is so strong in some of these markets that it is most unlikely to arise as mere chance. Yet even the statistical evidence might not be that convincing.

Consider a bag containing 99 black balls and one white one. What is the chance of picking out blindly the white ball? The answer is obviously one in a hundred. Now imagine having 100 chances, replacing the selected ball each time; what now are the chances of getting the white ball at least once? The chances clearly improve with each extra drawing and, in this case, the odds are better than evens that at least one drawing will produce the white ball. Clearly, plucking out the white ball becomes less remarkable the more dips are made.

Some fear that the results reported earlier by Bouman and Jacobsen are simply a more sophisticated version of the above dull game. Academics have been dipping into stock market databases for over a century now so it is not surprising that they can pull out such an anomaly. The anomaly would be remarkable if it had been discovered in the early days, but after a hundred years of trawling by a succession of academics and fund managers, an anomaly as strange as this was bound to appear (especially given the intensity of efforts being matched in recent decades by the scaling of computing power and the development of intensive search methods such as neural nets and genetic algorithms). This process, known in as "data mining" or "data snooping", invalidates the results. Researchers have long been wary of this, particularly when reporting calendar anomalies in stock markets but, as Lakonishok and Smidt (1988) make clear, it is difficult to allow for:

"*Data snooping is sometimes thought of as an individual sin ... However, it is also a collective sin. A hundred researchers using the same data test a hundred different hypotheses. The 101st derives a theory after studying the previous results and tests theory using more or less the same data*" (p. 405).

Data mining is a particular worry with stock price data, given the large industry of stockbrokers and fund managers seeking to exploit any perceived informational advantage it might give, however slight, due to its financial significance. An article in the *Journal of Econometrics* in November by Sullivan, Timmerman and White (2001) goes further than merely worrying about the possibility of data mining; they claim that all calendar anomalies can, in fact, be dismissed as such:

"*We find that although nominal p-values of individual calendar rules are extremely significant [i.e. pointing to a low probability that the result is due to mere chance], once evaluated in the context of the full universe from which such rules were drawn, calendar effects no longer remain significant*" (Abstract).

Their claim extends beyond calendar effects, indicating that stock prices contain little information to the current generation of researchers in this field: stock prices have been data mined almost to exhaustion.[6] In a working paper (Sullivan, Timmerman and White, 1999) they show the sort of discipline that should be exercised by the data-sharing scientific community to allow properly for data mining.

The above charge dismisses the earlier findings and suggests that if we adopt the "sell in May" rule as a trading strategy then it will breakdown. However the critique of Sullivan *et al*. is so powerful that it dismisses most evidence-based investing as being the results of data mining. What is the investor to rely on?

One of two things can be done. First, one can bide one's time until more data comes along and then test the trading strategy on the new data. However, it will take a long time to have confidence in the results as we only collect one pair of data points with each passing year to test the "sell in May" rule. The other, more attractive, alternative is to find a novel and reasonably independent data set that has not previously been investigated and use this as our testing ground. This latter approach is taken. In the next section, we introduce a virgin data set of market returns that are reasonably independent of market returns previously studied.

4. A TEST WITH VIRGIN DATA: THE IRISH CSO PRICE INDEX[7]

4.1 Description of Data

From January 1934 to the mid-1980s, the Irish Central Statistics Office (CSO) compiled a capital return index of Irish companies, *the CSO Price Index of Ordinary*

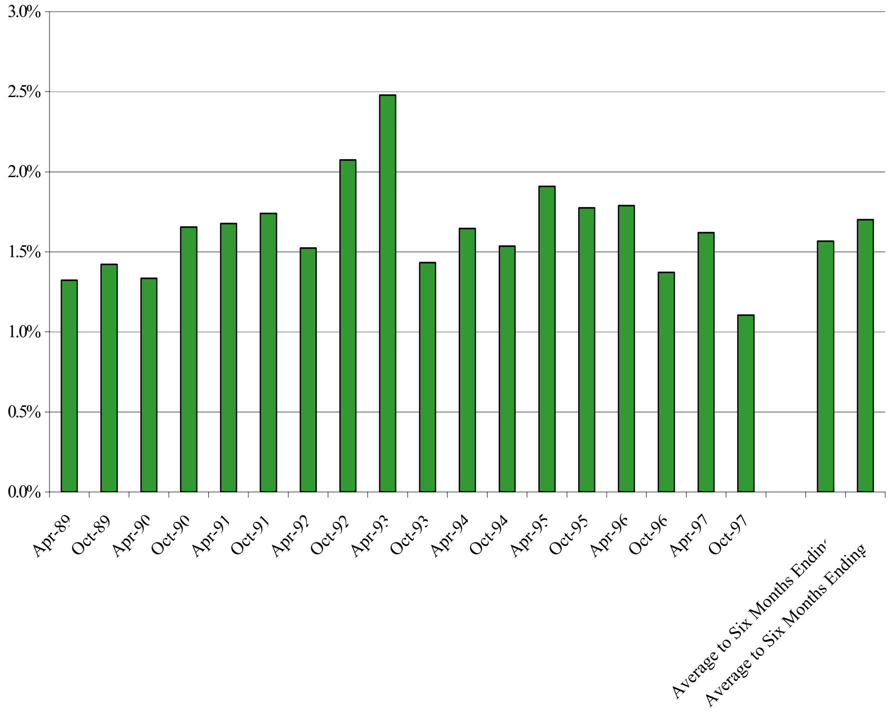
Stocks and Shares of Companies incorporated in Ireland (except Railways). We shall refer to this index in the sequel as the CSO Index. Details on the construction of the index are rather scant with, for instance, official sources such as the CSO itself, the annual *Statistical Abstract of Ireland* or its forerunner, the *Irish Trade Journal,* providing minimal descriptions. However, Geary (1944) describes it as an arithmetic, market-capitalisation weighted index with (at that time) complete coverage of the 88 non-railway Irish registered stocks listed on the two Irish exchanges of Dublin and Cork. This method of construction, optimum for our purposes, was unusual for that time with, for instance, the Dow Jones Industrial Average being a unweighted arithmetic average of thirty share prices or the British FT Ordinary Share Index being an unweighted geometric average of again just thirty share prices.

The CSO Index is calculated from share prices quoted on the Irish Stock Exchange on the first trading day of each month. There have been a few changes in its method of construction since 1934. Each January, beginning in January 1958, the index was adjusted to include only those shares that had been dealt in the previous twelve months. This entailed a reduction of the number of companies covered from 118 in January 1957 to 101 in January 1958 (Murray, 1960). In 1967 the index was again adjusted to include only companies with a market capitalisation in excess of IR£0.5 million (Kirwan. and Mcgilvray, 1983). Finally, the index was later superseded in January 1988 (Statistical Abstract, 1988) by the more comprehensive Irish Stock Exchange Equity (ISEQ) series of indices.[8]

Values of the CSO Index were obtained from successive issues of the *Statistical Abstract of Ireland* or its forerunner, the *Irish Trade Journal,* from which the complete series could be reconstructed. The CSO index was used up to the end of 1986. From the start of 1987, monthly values of the capital only ISEQ Overall Index were used. This gives a total of 805 data points, capturing the capital only return of the Irish equity market monthly from January 1934 to December 2000 inclusive.

Ideally, we would use an index with dividends reinvested so that the return measured the total return of capital and dividends combined. Dividends constituted the majority of returns to Irish equities in the period 1934-1960 (see Figure 4 and, for a contemporary account of their importance, Murray, 1960) so to ignore them could introduce a significant distortion, perhaps invalidating the results. The concern is whether there is a significant seasonal pattern in the timing of dividends. As dividends are customarily paid half-yearly (an interim and final), it would appear unlikely that there is a strong seasonality to their payments. The graph below shows the value of dividends as a percentage of the total capital value of the Irish index over nearly the decade to end October 1997, divided into the two six month periods. We find, as expected, a very minor variation between the six months to end October and the six months to end April – averaging over the period analysed just 0.1 per cent (that is 1.6 per cent to end October versus 1.7 per cent to end April). There is no pronounced seasonality in modern times and we assume that it was not a feature in earlier times.

Figure 3: Dividends (as percentage of capital value) payable in six months ending April and October, 1989-1997



The Irish index, rebased to start at 100, is graphed below up to the end of 1999 and compared with the UK FT 30 and the US Standard and Poor's Security Price Index.[9]

Figure 4: Capital only equity indices for US, UK and Ireland, 1934-2000, re-based, log-scale

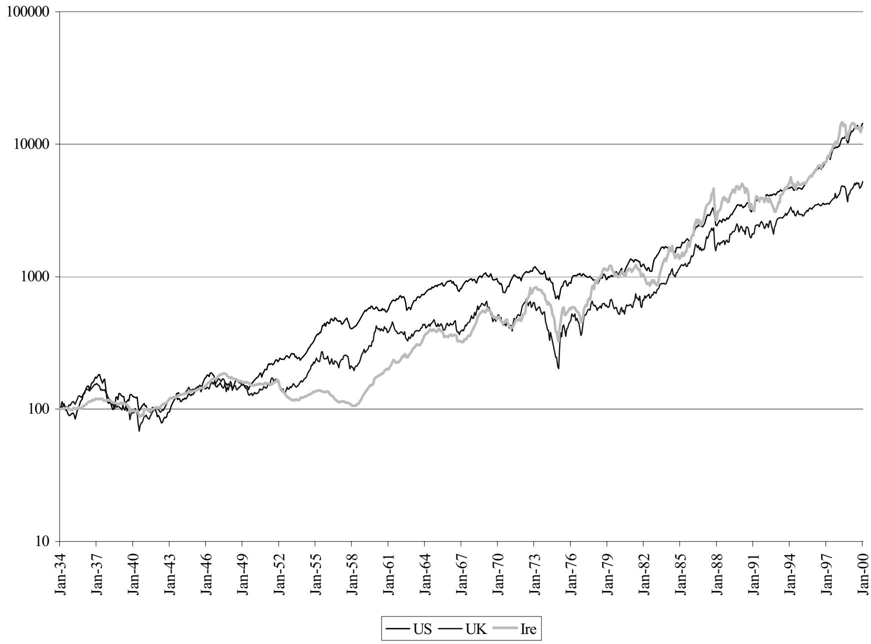


Figure 4 reveals that capital appreciation on the Irish equity market was modest from 1934 to 1960 with, in particular, the Irish market not participating in the post-war boom experienced in the US and the UK. The market staged a rally in the early 1960s, closing some of the gap. From the 1970s onwards, the Irish market shared the major ups and downs of the US and the UK – the 1973/4 crash, the 1987 crash and the bull trend since the early 1980s.

We are more concerned with the percentage change in the index than its overall level. The following page contrasts the rate of return (strictly, the log-return) in each month over the period 1934-99 with that delivered by the two major markets. The three graphs are standardised to facilitate visual comparison.

Clearly, the Irish market was considerably less volatile than the others up to 1960. The volatility increased markedly in the 1960s and again in the 1970s, and from about 1980 the volatility levels look similar to the high levels exhibited by the UK market. In particular, we note that the returns delivered by the Irish market over the entire period show a secular rise in volatility – the return series is obviously heteroscedastic.

Figure 5(a): Monthly log-returns on US equity market, 1934-2000

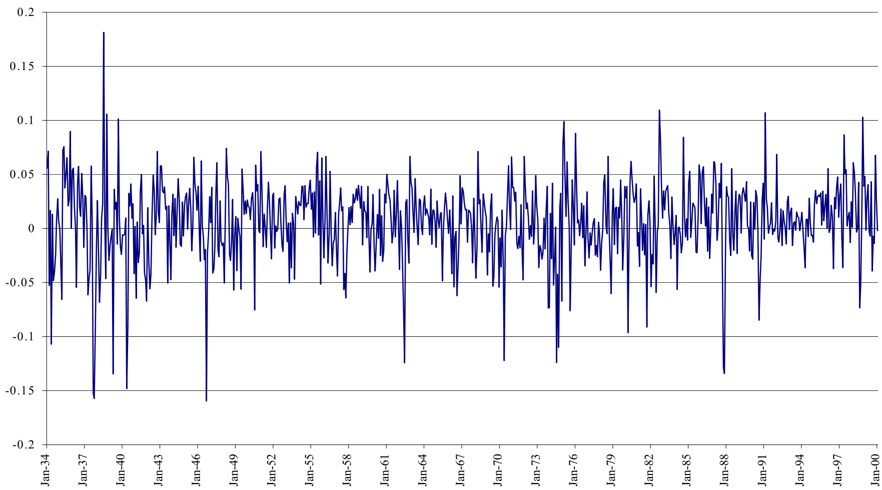


Figure 5(b): Monthly log-returns on UK equity market, 1934-2000

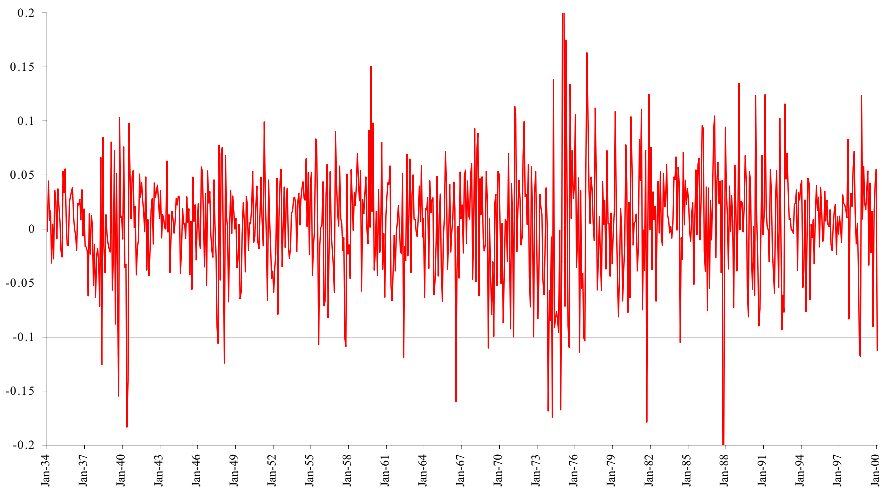
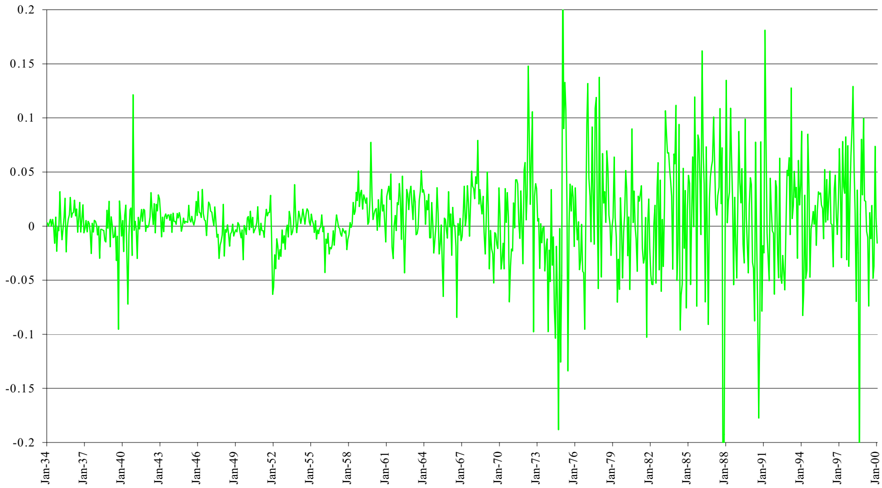


Figure 5(c): Monthly log-returns on Irish equity market, 1934 - 2000

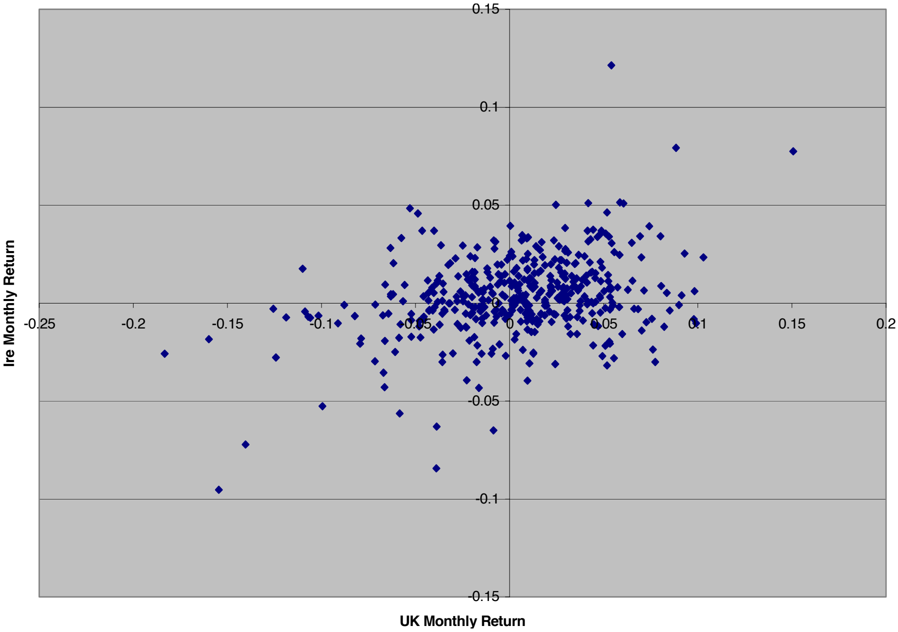


5. PRELIMINARY INVESTIGATION OF "SELL IN MAY"

We now investigate whether the trading strategy proposed by Bouman and Jacobsen would have worked in the Irish market. To ensure that our test is independent of those of Bouman and Jacobsen, we use as our primary data set the Irish market returns from 1934 to 1969. This was, as noted earlier, a period when the Irish market exhibited quite different trends and volatility to the two major markets and can therefore be regarded as a new test. A scatter plot of the monthly returns from the Irish market on the same month returns of both the UK and US markets give a simple demonstration of the near-independence of the Irish market in the period 1934 to 1969.

Figure 6(a) and (b): scatter plot of monthly equity returns January 1934 to December 1969

a) Ireland and UK



b) Ireland and US

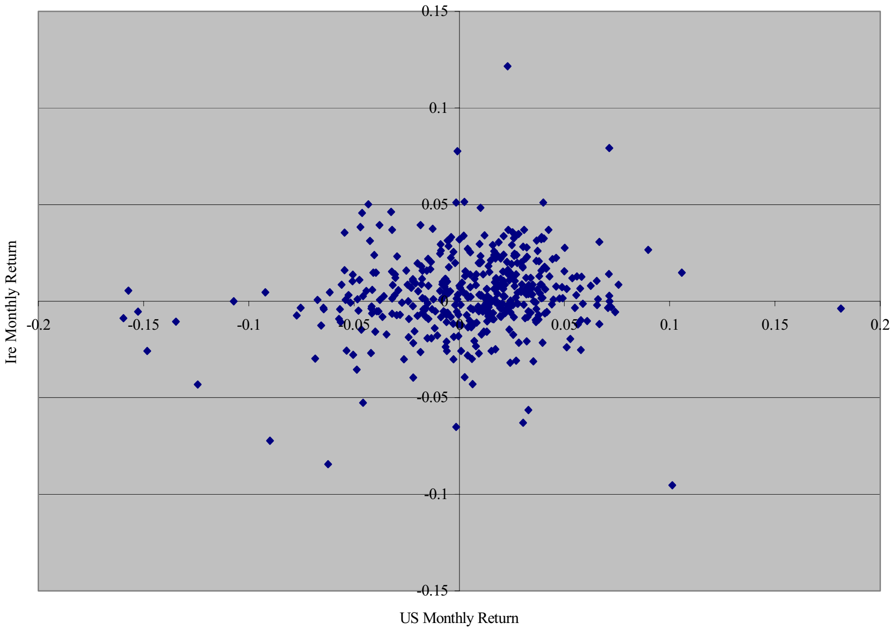


Table 1 divides the yearly return on the Irish market into that delivered in the six months to end April and the other six months to end October. Sample standard deviations are also shown to indicate the associated risk.

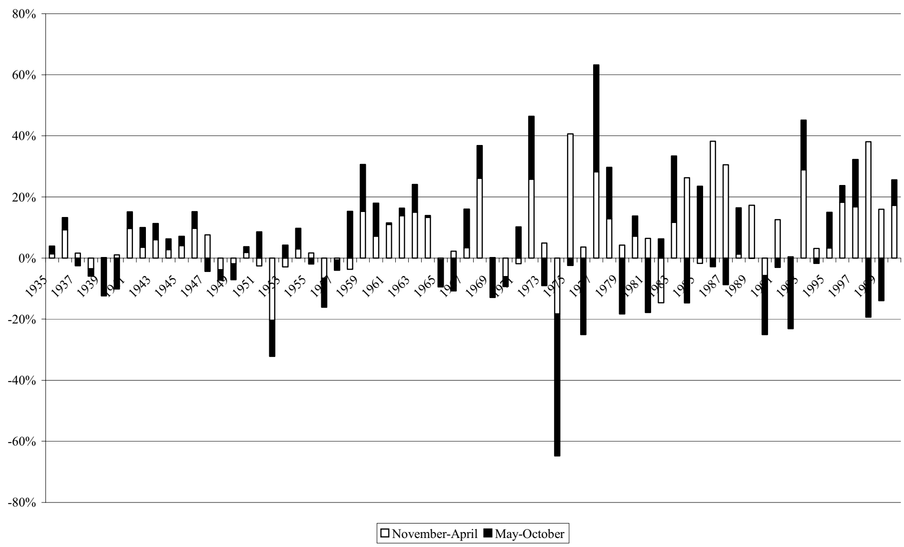
Table 1: Average returns and standard Deviation of Returns Ireland, UK and US: 1934-1999

		Ireland		UK		US	
		Nov-April	May-Oct	Nov-April	May-Oct	Nov-April	May-Oct
Average Return (%)	Jan 1934 – Dec 1969	3.5	0.9	3.9	-0.6	3.5	2.6
	Jan 1970 – Dec 1999	11.8	-0.8	12.3	-4.6	7.1	2.1
	Jan 1934 – Dec 1999	7.3	0.1	7.7	-1.7	5.1	2.4
Standard Deviation of Monthly Returns (%)	Jan 1934 – Dec 1969	2	2.1	3.8	5	3.3	4.3
	Jan 1970 – Dec 1999	5.7	6.3	6.4	5.9	3.5	3.6
	Jan 1934 – Dec 1999	4.2	4.5	5.2	5.4	3.4	4

The returns in half-year to end April are 2.6 per cent higher than the half-year to end October over the period 1934-69 (and the gap widens in more recent times). There is little or no difference in the standard deviation of returns between the two half-years with, if anything, the poorer performing half-year exhibiting a touch higher volatility. We conclude from Table 1 that the "sell in May" rule produces economic significant results, marginally so after allowing for trading costs.

A simple randomisation experiment can be used to estimate the statistical significance of the result.[10] From the previous considerations we take the January 1934 to December 1969 period as a new, out-of-sample, data source to test the statistical significance of the outcome observed above. Randomly drawing groups of 216 monthly returns with replacement from the total pool of 432 monthly returns in the period and repeating the process 10,000 times produced just 584 groups where the six-monthly returns averaged above 3.5 per cent and, coincidentally, another 584 groups where the six-monthly returns averaged below 0.9 per cent. This allows us to conclude that the probability of the observed seasonal pattern of returns between November and April and the other six months of the year being due to chance is about 6 per cent. The "Sell in May" adage demonstrates itself economically and statistically significant on our virgin data set. Finally, Figure 7 below illustrates the pattern the six-monthly returns formed over the last sixty-seven years.

Figure 7: Proportion of capital return on Irish equity market delivered in six months to end October and to end April compared, 1934-2000



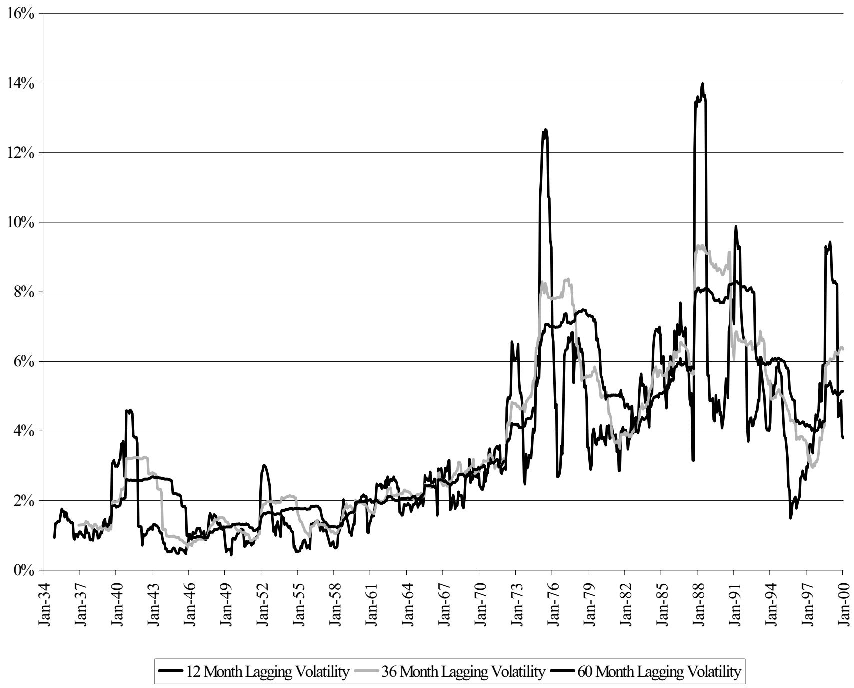
The earlier observation that the volatility of returns is evolving with time poses some challenge to the statistical analysis. This feature does not, of course, invalidate the economic significance of the results but it could lead to a misstatement of their statistical significance – it might be different, perhaps higher, than the 6 per cent cited above. In this application, the standard deviation of returns has the usual interpretation in financial economics as the risk of investing and, clearly, we would wish to standardise return per unit of risk. The impact of a secular trend in volatility (or market risk) on our results is softened by the observation that we are splitting each year into two six-month groupings hence, as is confirmed in the table, the overall level of risk ought be very close for each of the two sub-periods. However, we need to do a little more analysis to ensure that our statistical confidence in the results is well founded.

To counter the above reservation we need a test robust to the heteroscedasticity of the data. First, we note that the variance of the returns is likely to be approximately equal when the time periods are adjacent. This suggests that we compare the returns in one six month period with the average of the returns in six-month periods immediately preceding and following it. There are two ways to do this but, in our sample, both produce the same answer. The returns in the half-year ending April are higher in twenty-four out of the thirty-five comparison pairs in the period 1934-

1969. Now on the hypothesis that the returns in the two half-years are equal then the probability of observing a result as extreme as this is less than 2 per cent (using a two-sided binomial test).[11] This is highly suggestive that we are not overstating the statistical reliability of our findings due to presence of a secular rise in the variance of returns.

Another approach to attempt to ensure our results are robust to the observed heteroscedasticity is to attempt explicitly to standardise the variance of the series by dividing the return by the standard deviation of returns. The graph below shows how the sample variance of the time series of returns changes when calculated with monthly returns over the previous year, three years and five years.

Figure 8: Volatility measures of returns from the Irish equity market, 1934-2000



Let us suppose that the standard deviation at a given point in time is best estimated using the 36 monthly returns centred at that point, balancing the need of sufficient data points for statistical accuracy with a short enough time period to catch the trend of the changing parameter. Standardising the returns on this basis produces a series that not only removes the major secular trend in the variance but also removes some of the smaller eddies in the variances. We perform the simple randomisation experiment earlier on this standardised data set. Randomly drawing a set of 1,000 six monthly returns with replacement from the total pool of 415 standardised monthly returns in the period June 1935 to December 1969 produces 102 instances of returns in a six month period exceeding the average of the standardised returns observed in the six months ending April. In 122 cases the returns were lower than that observed in the six months to end October. Accordingly, we can conclude that after standardising the variance in the series, the statistical significance of the "Sell in May" rule is about 12 per cent.

These rough-and-ready tests on the data are suggestive that the abnormal profit from the trading rule is statistically significant at somewhere in the range 2-12 per cent. We further investigate these results in a more formal setting in Appendix I and come to a similar conclusion.

One final word of warning on data mining is pertinent and can be put as a question: What are the chances that this paper would be read before this Society if the results were negative – that is, if the outcome of our investigations had not supported the Bouman and Jacobsen strategy? We, the authors, doubt that we would have put the effort into writing up such a negative result and, even if we had done so, the resultant paper would hardly have passed the scrutineering process for papers read to this Society. Thus we have an implicit filtering process before the results are presented to you, and this filtering process is dependent on the result of our investigation. This is another, subtle, incidence of data mining that we cannot allow for but must be considered by anyone considering employing the trading strategy investigated. As always, *caveat emptor* applies to those investing – or disinvesting – from equity markets.

6. FURTHER INVESTIGATION OF MONTHLY SEASONALITY IN EQUITY MARKETS

The previous analysis confirms the existence of a seasonal pattern in the returns delivered by equity markets and the improbability that this can be accounted for by happenstance or data mining. In this section we explore this seasonality a little further by analysis at the monthly level.

6.1 Review of International Literature on Monthly Seasonality

A significant body of literature already exists to suggest that, especially for smaller capitalisation stocks, returns vary significantly across the months of the year. Most typically, the evidence is that high returns can be earned in January, especially the early part of January. The conclusion from these studies is, however, directly challenged in Sullivan, Timmerman and White (2001)

Early evidence on the tendency of January returns to exceed those of other months comes from Wachtel (1942), with a large hiatus until Officer (1975) and Rozeff and Kinney (1976) revisited the phenomenon. From the evidence presented in Rozeff and Kinney (1976) and Gultekien and Gultekien (1983), unusually large returns in January can be traced back to 1904. Much of the discussion on the January effect co-exists with the issue of whether a size effect, the phenomenon whereby small-capitalisation firms earn superior returns to large-capitalisation firms, exists and if so, when it manifests itself. From the pioneering work of Banz (1981) and Reinganum (1981), through Brown *et al.* (1983) and Kato and Schallheim (1985), Fama and French (1992), Berk (1995), Baker and Limmack (1998) and Garza-Gomez, Hodoshima and Kunimura (1998), it has been a consistent finding that small capitalisation firms produce higher returns than those with higher capitalisations.[12] Evidence from Keim (1983) and Roll (1983) indicates that the majority of the return to small capitalisation stocks occurs in January, indeed being concentrated in the first weeks of the month. The significant findings in the early 1980s are collected in Dimson (1988). Agrawal and Tandon (1994) examine, over the 1970s and 1980s, 19 countries in total finding that the mean January returns are high. In 11 instances a non-parametric Kruskal-Wallis test rejects the hypothesis of equality of monthly mean returns.[13] The typical return to January (from Table 6), appears to be in the 3 per cent to 6 per cent range, with other months returning much lower rates. An important recent survey work that synthesises the international findings is Hawawini and Keim (2000) who show that returns in January are so anomalously high relative to other months that, if used as a explanatory variable, better accounts for cross-sectional returns of stocks than the beta of CAPM or some of the data-driven models proposed in recent times.

In appendix II we briefly review the evidence of monthly seasonality in equity markets around the world. The survey draws on a large number of independent studies, which vary both in the period analysed and the statistical methodology used and, hence, in the reliably of the reported findings. January returns do appear to be most frequently the highest, often statistically so, but other months are mentioned as exhibiting or having exhibited superior returns such as April and February.

6.2 Monthly Seasonality in the Irish Equity Market

Previous evidence on monthly returns in Ireland arises from a small number of papers. Mckillop and Hutchinson (1989), Donnelly (1991), Gahan (1993) and Lucey (1994) have all addressed the issue of the seasonal pattern of returns. McKillop and Hutchinson (1989) examine April and August returns in the context of small firms. They find that an April effect, but not an August effect. A more detailed examination is that carried out in Donnelly (1991). He uses the CSO index over the 1951-1988 period, splitting the data into pre- and post- 1969 samples. Overall, the evidence is that January returns are substantially larger than those in other months. A return of 2.77 per cent overall compares to the next highest monthly return overall (April) of 2 per cent. A shorter time span is investigated in Gahan (1993), that of 1983-1993. She finds for the ISEQ index that January returns are again the highest, at 6.86 per cent; the next highest month (February) showed a return of 3.97 per cent, with April being the third highest at 2.79 per cent. In only three years was January not the month showing the highest return. Finally, over a shorter time period again, the work of Lucey (1994) again investigates the ISEQ index, this time over 1987-1991. In common with Donnelly (1991) January daily returns, at .00306 per cent are the highest, February (.0025 per cent) being the second highest. In contrast to both Donnelly (1991) and Gahan (1993), April returns are negative and close to zero.

We now investigate monthly seasonality of returns from the Irish market and relate the findings to our "Sell in May" trading strategy.

The graph and table below summarise the average capital returns on the Irish market each month over the last 70 odd years. The standard deviation of returns in each month is shown alongside as the standard measure of risk.

Figure 9: Mean and standard deviation, CSO returns: calendar month, 1933-2000

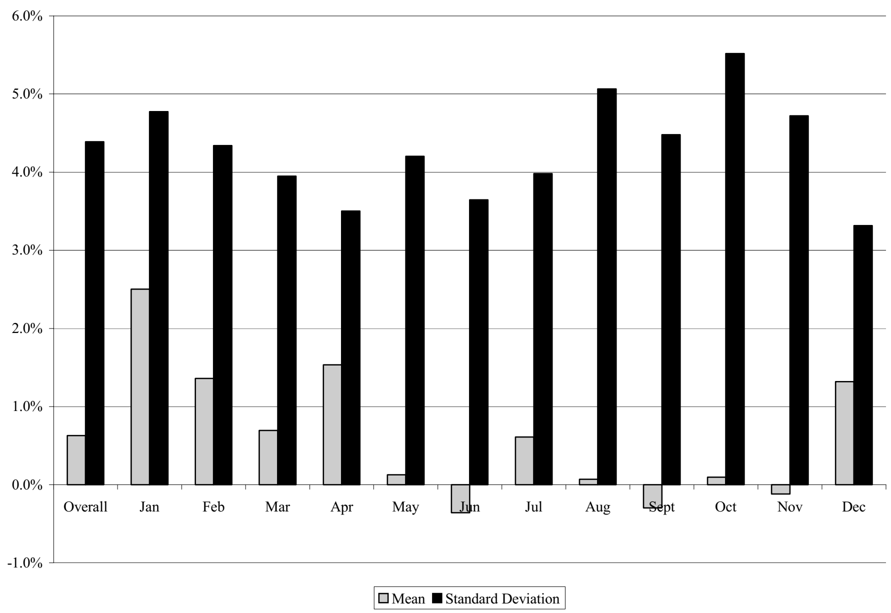


Table 2: CSO returns by calendar month, average return and higher order moments, 1934-2000

	Mean (%)	SD (%)	Skew	Excess Kurtosis	50% Trun. Mean (%)	75% Trun. Mean (%)	90% Trun Mean (%)	Median (%)	Count
Jan	2.5	4.8	1.9	6.5	1.6	1.9	2.2	1.2	67
Feb	1.4	4.3	1.6	4.8	0.9	0.9	1.0	0.6	67
Mar	0.7	4.0	1.1	1.8	0.4	0.3	0.4	0.3	67
Apr	1.5	3.5	1.2	3.7	0.8	1.0	1.3	0.8	67
May	0.1	4.2	-0.1	0.6	0.4	0.2	0.1	0.5	67
Jun	-0.4	3.6	-0.8	2.1	-0.1	-0.1	-0.2	-0.1	67
Jul	0.6	4.0	0.9	1	0.0	0.2	0.5	0.1	67
Aug	0.1	5.1	-1.9	7.1	0.7	0.6	0.4	0.5	67
Sept	-0.3	4.5	-1.2	4.4	0.4	0.2	-0.1	0.3	67
Oct	0.1	5.5	-4	25.6	0.4	0.5	0.6	0.1	67
Nov	-0.1	4.7	-1.1	4	0.4	0.3	0.1	0.2	67
Dec	1.3	3.3	1.1	2.8	0.9	1.0	1.1	0.6	67
Total	0.6	4.4	-0.6	9.3	0.9	0.6	0.6	0.4	804

A significant January premium seems to be a feature of the Irish market. Again, a simple randomisation experiment can be used to estimate the statistical significance of the observed January premium. Randomly drawing 67 monthly returns with replacement from the total pool of 804 monthly returns, and repeating the process 1,000 times did not produce a single instance of an average return matching or exceeding that observed in January (the largest was 2.44 per cent). In the same simulation, 8.7 per cent exceeded the 50 per cent truncated mean, 2.7 per cent exceeded the 75 per cent truncated mean, 0.5 per cent the 90 per cent truncated mean, and 1.4 per cent the median. All measures of the centre of the distribution highlight the unusual large value in January. Of the higher order moments, only the skewness appears unusual: the standard deviation observed in January was exceeded in 27 per cent of randomised drawings, the skewness in 3.2 per cent, and the kurtosis in 22 per cent. If only the market returns to the end of 1969 are regarded as providing an independent test of the January effect then 10,000 random drawings of 36 monthly returns produce just 56 instances of the average return exceeding that recorded for the 36 Januaries in the period – the effect is still very significant statistically.

Given two distributions, the condition that

$$F_1(x) \leq F_2(x), \forall x$$

is described as the first order stochastic dominance (FSD) of $F_1(x)$ over $F_2(x)$ Applied to our case, a return distribution that first order dominates another is preferred by any wealth maximiser regardless of their utility function. A less stringent condition is second order stochastic dominance (SSD), with $F_1(x)$ said to dominate $F_3(x)$ by SSD if and only if

$$\int_{-\infty}^{x} F_1(y)dy \leq \int_{-\infty}^{x} F_3(y)dy, \forall x$$

Investors who are both nonsatiated and risk averse prefer the payoff of $F_1(x)$ over $F_3(x)$. The return premium for January and its pronounced positive skewness suggests that the return in January might stochastically dominate (either by FSD or SSD) the returns for all other calendar month. The table below reports the results of this investigation, demonstrating that January returns exhibit FSD over eight other calendar months and SSD over another one.

Table 3: Order of stochastic dominance of January returns over other calendar months

	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan over other months	SSD	FSD		FSD	FSD	FSD	FSD	FSD	FSD	FSD	

These results highlight that the January effect in Ireland, when investigated using stochastic dominance, is more pronounced in Ireland than reported by Sehun (1993) for the value-weighted portfolio of NYSE firms, 1926-1991.

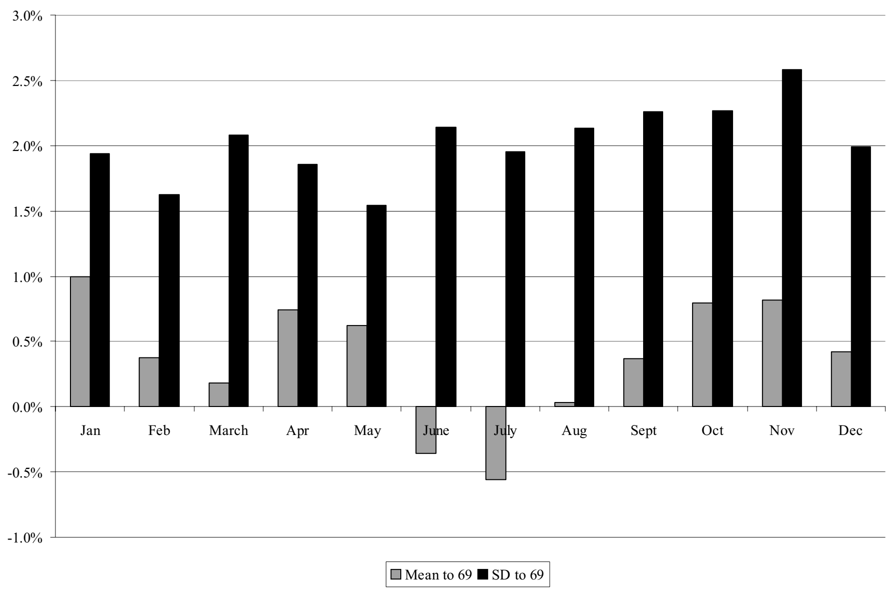
We further investigated other months that exhibit notable stochastic dominance and report in the table below that December, February and April also tend to dominate the summer and autumn months.

Table 4: Order of stochastic dominance of December, February and April returns over other calendar months

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Dec over other months					SSD	FSD	SSD	SSD	SSD	SSD	SSD	
Jan over other months		SSD	FSD		FSD	FSD	FSD	FSD	FSD	FSD	FSD	
Feb over other months					SSD	FSD		SSD	FSD	SSD	SSD	
Apr over other months					SSD	FSD		SSD	FSD	FSD	SSD	

It seems that returns in January are unusually high but so are the returns in December, February and April. Rather than report the results as a monthly effect it seems that they may be better reported as a half-yearly effect – the half-yearly effect identified by Bouman and Jacobsen. We investigate this contention below.

Figure 10: Mean and standard deviation, CSO returns, calendar month, 1934-1969



Making 10,000 randomly drawing of 36 monthly returns from the half years periods ending April in every year, 1934 to 1969, and averaging the results produced 1181 instances of the return exceeding the average of the 36 January returns in this period. This implies that tested out-of-sample and after allowing for the half-yearly effect identified in Jacobsen and Bouman (2001), the January effect is significant only at the 12 per cent level in a one-sided test. The graph above highlights this where we see that, though the January return is higher than any other month, it is not so out of line with monthly returns in the half year ending April.

7. CONCLUSION

We confirm the findings of Jacobsen and Bouman (2001). Capital returns in the Irish market have indeed been higher in the winter and spring months than the other two seasons. From 1934 to 1969 the capital return averaged 3.5 per cent annum in November-April compared to 0.9 per cent in May-October. Since 1970 it has been a pronounced feature, with the November-April return averaging 11.8 per cent over the last thirty years against the average over May-October of –0.8 per cent. Only the return prior to 1970 can be represented as an independent test of the trading strategy of "Sell in May but buy back at Halloween" and as such it provides confirmation that the rule is economically significant (marginally so after allowing for trading costs) and, using a number of tests, we find the result to be reasonably significant statistically. Accordingly we commend the aphorism "sell in May and go away" but buy back at Halloween to investors in the twenty-first century as a plausible strategy to outperform the average risk-adjusted return on equity markets.

In particular, this paper provides an out-of-sample test of seasonality in equity markets and finds evidence supporting the hypothesis that the price formation process does indeed have seasonal features. Accordingly, the contention in Sullivan, Timmerman and White (2001) that such findings are a result of data mining is rejected.

We further overview other calendar month anomalies frequently reported in the finance literature with our novel data set. We find that the abnormally high returns reported frequently for January and April, and occasionally in February and other months, are also a feature of the Irish market but contend that these seasonalities are perhaps better and more parsimoniously ascribed to the half-year effect documented by Bouman and Jacobsen.

Endnotes

1. See, for instance, Bernstein (1992) or, for a more concise overview of the development, Dimson and Mussavian (1998).
2. "Heads, Shoulders and Broadening Bottoms", The Economist, 19 August 2000, p. 76.
3. The Sunday Times, "Professors Head for Wall Street", 12 November 2000.
4. If we were to hazard a guess we would date it from the first half of the nineteenth century when the St. Leger was the most popular of all race meetings and was not without controversy. For instance, in 1819 it was run twice when the favourite was injured in last minute training, prompting punters to race to distant betting towns to place their bets at favourable odds (the rerun was later overruled by the Jockey Club). Again, in 1829, there was widespread unruly behaviour and several particularly unsavoury characters were "chased out of town". The timing of the St. Leger Sweepstakes, run every September, would probably have been very widely known at this time.
5. Bouman and Jacobsen study two more markets with somewhat shorter histories, Brazil and Russia, and record that it works on these markets too. They also demonstrate that the results are robust when returns are risk-adjusted and hold when the stock market crash of 1987 is ignored. Finally, they attempt to explain the observed seasonality in returns but cannot, they admit, find a convincing explanation.
6. Having said that, they do find some technical trading rules that work, even after allowing for the intensity of the search. Typically, they remain coy on the rules (Sullivan,. Timmerman and White, 1999).
7. Perhaps it is better described with the oxymoron "near virgin" data set. To our knowledge, only Donnelly (1991) and Whelan (1999 and 1999b) have ever studied this index, the latter two studies unconnected with seasonality. Donnelly documents a January and April effect over the period 1951-1988.
8. For full description of this later index is given on the Irish Stock Exchange's website at www.ise.ie. Briefly, it is a capitalisation weighted arithmetic index of all the stocks listed on the Irish Stock Exchange with a registered office in Ireland.
9. For the index for the US see Shiller (1992), Chapter 26, as updated on his website. Values for the FT 30 were obtained from Global Financial Data (www.globalfindata.com).
10. Non-parametric tests are preferable, say, to those which presuppose Normality, as equity return distributions are known to be thick-tailed (see, for instance, Whelan (1999) for an investigation of the tail behaviour of the CSO Index).
11. Over the full period 1934-2000, we count 46 instances out of a total possible 66 that the return over six months to end April exceeded the average of the immediately preceding and proceeding six months (45 instances if we compare the average of the two half year returns either side of the half year ending October). The probability that this is a chance outcome, assuming the returns are equal in the six month periods, is less than 0.2 per cent.

12. See, however, Dimson and Marsh (1999), who examine UK data and find that the small firm premium has reversed in the 1990s.
13. Belgium, France, Hong Kong, Italy, Japan, Netherlands, Singapore, Sweden, Switzerland , UK and US.

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APPENDIX I:
FURTHER INVESTIGATION OF THE STATISTICAL SIGNIFICANCE OF THE "SELL IN MAY" RULE

A formal test of the existence of monthly calendar effects in mean returns is given by the ANOVA or Kruskal-Wallis statistics. This test is designed to evaluate the hypothesis that the populations from which the samples are drawn have identical distributions, and is particularly sensitive to differences in means. It can also be loosely described as a test for whether the different populations have the same mean. It is a joint test however; if the test indicates that the hull hypothesis is not feasibly held then we cannot know, without further investigation, what is the cause of the differences in population.

Let R_j^2 be the average rank of observations (returns of the index in this work) in the j^{th} group (each month of the year) and n_j be the number of observations in the j^{th} group. Then, with k groups and N observations in total, the Kruskal–Wallis statistic is:

$$H = \left(\frac{12}{N(N+1)} \sum_{j=1}^{k} \frac{R_j^2}{n_j} \right) - 3(N+1)$$

distributed as a χ^2 distribution with (k–1) degrees of freedom.

The Levene test tests the following hypotheses:

$$H_0: \ \sigma_i = \sigma_j \ \forall i, j$$

H_A: $\sigma_i \neq \sigma_j$ for at least one i, j pair

The test statistic is defined as:

$$W = \frac{(N-k)\sum_{i=1}^{k} N_i \left(\overline{Z_i} - \overline{Z_j}\right)^2}{(k-1)\sum_{i=1}^{k}\sum_{j=i}^{N}\left(Z_{ij} - \overline{Z_i}\right)^2}$$

where

1. $Z_{ij} = \left| Y_{ij} - \overline{Y_i} \right|$, $\overline{Y_i}$ the mean of subgroup i
2. $Z_{ij} = \left| Y_{ij} - \widetilde{Y_i} \right|$, $\widetilde{Y_i}$ the median of subgroup i

3. $Z_{ij} = \left|Y_{ij} - \bar{Y}_i^{10}\right|$, $\bar{Y}_i^{10}$ the 10 per cent trimmed mean of subgroup i

the above being the three choices for defining which Z_{ij} determine the robustness and power of Levene's test.

The definition based on the median is the choice that provides good robustness against many types of non-normal data but retains good power, and so is the one used here. The Levene test rejects the hypothesis that the variances are homogeneous if $W > F_{(1-\alpha,\, k-1,\, N-1)}$ where $F_{(1-\alpha,\, k-1,\, N-1)}$ is the upper critical value of the F distribution with (k–1) and (N–1) degrees of freedom at a significance level of $\propto$.

In order to examine both the existence and temporal stability of any profitable trading rule or monthly seasonal patterns, the data were analysed both in aggregate and in sub-periods. The periods were chosen so to balance

a) the need for enough data to remain within each period that meaningful statistical analysis could be made;
b) the need to ensure that the periods chosen represented broadly homogenous economic and political regimes in the Irish economy, so that the variance of returns might be reasonably homogeneous.

Of course, given the charge of data snooping addressed above, one initial split in the data was into pre- and post- 1969. We adopted twelve years as the length of the sub-groups and rationalise the resulting partition as follows:

- 1934-1945: when Ireland attempted a higher degree of self-sufficiency in the context of a collapse of world trade, economic war with its dominant trading partner, and the autarky enforced by the “Emergency”;
- 1946-1957: captures the continuation of the pre-War policies, despite a revival in world trade and Ireland’s poor comparative economic performance;
- 1958-1969: captures the early opening of the Irish economy (post-Whittaker);
- 1970-1981: captures the turbulence of two oil shocks, high inflation and high borrowings;
- 1982-1993: captures Ireland increasingly following the external discipline imposed by floating the Irish pound and attempting to become part of the founding currencies of the euro;
- 1994 onward: captures Ireland’s extraordinary recent growth period.

Table 1 and Table 2 analyse the “Sell in May but buy back at Halloween” strategy advocated by Jacobsen and Bouman (2001). From the tables, it is clear that the returns in the first half of the year, from November to April, are greater in magnitude than those of the second half of the year in all but the 1946-57 period. The Kruskal-Wallis test does not indicate that this effect is statistically significant, but the

ANOVA test does. This is true in all bar one sub-period and, from the Levene test, this cannot be attributed to differential risk profiles within these periods.

Table 1: The "Sell in May but buy back at Halloween" trading rule in Ireland 1934-2000

		34-45	46-57	58-69	70-81	82-93	94 on	Overall
Mean	May-Oct	0.00	-0.18	0.62	-0.46	0.15	0.14	0.14
	Nov-Apr	0.56	-0.30	-1.50	1.48	2.09	2.49	2.49
Std.	May-Oct	0.019	0.014	0.027	0.056	0.071	0.056	0.056
	Nov-Apr	0.019	0.016	0.022	0.058	0.063	0.044	0.044
Skewness	May-Oct	-2.643	0.221	-0.569	-0.404	-1.831	-1.563	-1.563
	Nov-Apr	3.314	-1.332	-0.147	1.173	-0.233	0.044	0.044
Kurtosis	May-Oct	10.189	0.524	1.592	1.054	7.503	4.947	4.947
	Nov-Apr	20.576	3.326	0.214	3.429	1.18	0.164	0.164

Table 2: Half year effects (half-years to end April and end October) in the first two moments by sub-period, Irish equity market 1934-2000

	Kruskal-Wallis Test Statistic	Marginal Significance	F Stats	Marginal Significance	Levene Statistic	df1	df2	Marg Sig
34-45	0.27	0.603	3.158	0.078	0.398	1	142	0.529
46-57	0.031	0.86	0.244	0.622	0.085	1	142	0.771
58-69	4.484	0.034	4.63	0.033	1.389	1	142	0.24
70-81	2.554	0.11	4.18	0.043	0.007	1	142	0.932
82-93	1.824	0.177	2.977	0.087	0.458	1	142	0.5
94 on	2.313	0.128	4.509	0.037	0.99	1	82	0.323

APPENDIX II:
A BRIEF REVIEW OF STUDIES OF MONTHLY SEASONALITY IN EQUITY MARKETS

US

Much of the work on monthly seasonality in the US has been driven by an examination of "January effects". Rozeff and Kinney (1976), using data from 1904 to 1974, found that in the mean January returns in the US market was the largest of all months, and that this observation was robust over most sub-time periods. The mean daily return in January overall was 0.0348 per cent, compared to the next highest month, July, at 0.0190 per cent.[1] Work by Lakonishok and Smidt (1988) on the large capitalisation Dow Jones index, from 1897 to 1986 , showed however that the January return of 0.818 per cent was in fact the fourth largest return after July, August and December. This is consistent with the results on the interrelationship of the size and month issue, as discussed in Keim (1983) and Reinganum (1983). The evidence shows clearly that the excess returns in January in the US market is confined to the smaller stocks. Haugen and Jorion (1996) examined the CRSP indices for the New York Stock Exchange from 1926 to 1993, and showed that the return in January to the smallest stocks is of the magnitude of 12.4 per cent, falling monotonically to as little as 0.5 per cent for the very largest stocks. More recent work (Riepe, 1998, 2001) has indicated that excess returns in January may be declining in latter years.

UK

Evidence on the magnitude of monthly seasonal patterns in the UK can also be found in a wide variety of papers. One of the earlier papers focussing primarily on the UK market was Reinganum and Shapiro (1987). They found, using a variety of data sources, that April returns dominated in the period prior to the introduction of capital gains taxation in 1965, while after 1965 January returns were the largest in the year. For example, using the FT-A index the January return over the period April 1965-December 1979 was 5.18 per cent, compared to the next highest month, April, with a return of 3.85 per cent. Using a different dataset, the FT-SE indices, Mills and Coutts (1995) found that over the January 1986-October 1992 period, the mean return to January was the largest of any month. For the FT-SE 100 index, mean January daily returns were 0.159 per cent as against the next highest return of 0.136 per cent (February). The FT-SE 250 index, on the other hand, showed a February return of 0.196 per cent as the highest, with January being the second highest at 0.190 per cent. In both cases, the April return, so significant in the results of Reinganum and Shapiro (1987), was low and insignificant. Examining the FT30 index over the 1935-1994 period, Arsad and Coutts (1997) found results confirmatory to Reinganum and Shapiro (1987). Overall January returns, at 0.104 per cent, were the highest of all months.

Continental Europe

Evidence on seasonality in the Amsterdam exchange from January 1966-December 1982 is contained in Van Den Berg and Wessels (1985), who found that January mean returns amount to 4.39 per cent, the highest of any month, the second highest being April at 3.15 per cent.

For the Milan exchange over the 1975-1989 period, results are presented in Barone (1990). There, the January mean daily return at 0.33 per cent is the highest of the year, with February and September tying for second place at 0.24 per cent. A test over a longer period is presented in Canestrelli and Ziemba (2000), who examined the 1973-1993 period with sub period analysis. There, the mean daily returns in January and February were significantly higher, at 0.258 per cent and 0.205 per cent respectively, than other months. The only other month that was statistically significantly different from zero was August, with an average return over the period of 0.116 per cent. These patterns also held over sub periods.

Evidence on the Spanish market presented in Santesmaes (1986) indicates that February, not January, presents the highest return for the short period 1979-1986 period.

Asia and Pacific

Results for Japan can be seen over a long period, 1949-1994, by combining the findings of Ziemba (1991) and Comolli and Ziemba (2000). There, the evidence indicates that over the 1949-1988 period, January mean daily returns averaged 0.182 per cent, considerably above the next month, August, at .079 per cent. For the 1990-1994 period this dropped somewhat; January mean daily returns now averaged 0.052 per cent, with the highest monthly mean return being October at 0.189 per cent.

As noted, the work of Officer (1975), drawing on earlier work (Praetz, 1973), was one of the first “modern” academic papers to examine seasonality, in this case relating to Australia. The paper did not indicate monthly returns, examining instead lag and correlation patterns. It did, however, allude to a January-February peak in the market. More detailed data for the Australian markets is to be found in Brown *et al.* (1983). Examining data from 1958-1981, they found that January returns are in fact the highest, a monthly average return of 3.14 per cent, with this being the case across a variety of size measures. Again, as found in Berges, McConnell and Schlarbaum (1984), this is larger in small capitalisation stocks.

In south-east Asia, the results of Ho (1990) analysing the 1975-1987 period indicated that out of twelve markets analysed, including the US and UK, ten have significant January returns.[2] For the south-east Asian countries which show a significant January return, these returns typically exceed the mean of all other months by 10 to 20 times. This pattern, of high and statistically significant daily January returns, is confirmed for Hong-Kong, Korea and Taiwan in Wong *et al.*

(1990). However, for both Taiwan and Korea, the evidence from Tong (1992) is that February (for Taiwan) and May (for Korea) returns are the highest. Chan, Khanthavit and Thomas (1996) present contradictory results to Ho (1990). They analyse returns in Malaysia, India, Singapore and Thailand from 1974 to 1992, and find that only for Malaysia and Singapore are there significant January monthly returns. In addition, it is only for these markets that a test of equal monthly returns is rejected. It is, however, only in Singapore that the highest monthly return occurs in January; for Malaysia it is December (0.195 per cent), for India, February (0.306 per cent), and for Thailand, April (0.176 per cent). Malaysian results are further complicated by the results of Wong *et al.* (1990); they present results for the Kuala Lumpur stock exchange which indicate that the return in January is among the highest of all months, over the 1970-1985 period on six sectoral indices. The January return was, in fact, the highest in three of the six indices and in a value weighted index of large firms.

Other Markets

For the Johannesburg stock exchange Coutts and Sheik (2000) report a January return which is negative and statistically insignificant from zero. While no overall month is indeed significant statistically, the month that demonstrates the highest mean daily return is June, at 0.186 per cent. For Jamaica, Ramcharran (1997) finds no January seasonality, with the month of May instead showing the highest return. January returns were, in fact, at or close to the mean across the 1874-1994 period examined.

Endnotes

1. One difficulty with this, however, is that the paper combines into one data series a set of three different indices. Some of these were equally weighted; others value weighted. Evidence from Theobald and Price (1984) shows that seasonality is more easily detected in equally weighted data.
2. Namely, Hong-Kong, Japan, Korea, Malaysia, Philippines, Singapore, Taiwan and Thailand, as well as the UK and USA