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Calendar “anomalies” in the Portuguese stock market

ABSTRACT

In this paper we search for calendar regularities in the Portuguese stock market. We did not find the Weekday or the January “anomalies” but other significant regularities were found which constitutes evidence against market efficiency. The significant “anomalies” were the Pre-holiday effect (where average returns are twelve times higher the other days’ returns) and a Turn-of-the-month effect. Statistically, the most robust of these “anomalies” is the Holiday effect but, economically, the most significant is the Turn-of-the-month effect.

1. INTRODUCTION

The investigation of calendar patterns or seasonality in stock returns is certainly a classic study in the finance field. Probably because it is interesting to investigate and understand these curious patterns or “anomalies”, because it can be done with minimal data requirements but also because we may be able to draw some conclusions regarding market efficiency with this research. Actually, a (consistent) seasonal pattern represents evidence against the weak-form market efficiency since it would imply return predictability. At a practical level, investors can build trading strategies based on consistent seasonality or, at least, they can determine favourable market entry and exit moments.

Many kinds of calendar “anomalies” have been found but the most popular (or recurrent) are the Day-of-the-week effect (or Weekday effect, Weekend effect, or most of the times, the Monday effect)[1], the January effect (or Turn-of-the-year effect), the Turn-of-the-month effect and the Holiday effect. The Day-of-the-week effect refers to significant return differences (higher or lower) between the days of the week. The January effect is concerned with the abnormally higher returns during this month and the Turn-of-the-month effect refers to the patterns on the last days and the first days of any month. The Holiday effect refers to the abnormal stock returns before and/or after holidays.

In this paper we analyze these effects for a long sample (1989-2008), in what we believe to be the most exhaustive study for the Portuguese stock market. To study the Day-of-the-week and the January effect we use the standard OLS (Ordinary Least Squares) regressions with dummies and tests for the equality of means (F-tests and the Kruskall-Wallis test). The Turn-of-the-month and the Holiday effect are studied with the T-test and the Mann-Whitney test for equality of means. Several robustness checks will be performed.

We found some evidence against market efficiency although concerns on the stability of the patterns may cloud this evidence. Nevertheless, the interesting results found deserve attention. For instance, regarding the Holiday effect the daily average return in our 20-year period is 0,186% in the days before holidays, 0,137% in the days after holidays and only 0,0105% in other days. Excluding days before holidays, January has an average daily return of 0,087%, February 0,136% and the other days average -0,003%. In addition, excluding days before holidays, the average daily return around the turn-of-the-month was 0,095% against a negative average return of -0,003% in the other days.

We found that trading rules based on these patterns, before transaction costs, would be superior to simple buy-and-hold strategies. Of course, trading strategies implemented to exploit these “anomalies” would carry transaction costs but we believe that they would not be excessive (nowadays). For instance, in a typical calendar year, presently, the stock market closes only during six or less holidays. Accordingly, a trader would have to make 12 (buy and sell) transactions per year to exploit this regularity and the Turn-of-the-month effect would be exploitable with 24 transactions per year, for example. Considering, additionally, that the regularities were found using market indexes and that there is a tradable futures contract on one of these indexes we believe that transaction costs would not impede such strategies.

The organization of this paper is as follows. Section 2 briefly reviews the literature emphasizing potential explanations for these “anomalies”, Section 3 presents our data and Section 4 discusses our methodologies and results. In Section 5 we try to validate our previous results with several robustness checks. Section 6 briefly explores the economic significance of our results and Section 7 concludes the paper.

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[1] There is a difference between the Monday and the Weekend Effect. If we measure the change between the Friday close and the Monday opening price we are studying exclusively the Weekend effect but if we measure the change between Friday close and Monday close we are measuring a combined Weekend and Monday effect.

2. BACKGROUND

The first references to calendar “anomalies” in the U.S. date back to the beginning of the 20th century. Pettengill (2003) mentions that the January effect was already referenced in 1919 and Maberly (1995) found that the Monday effect was already documented in 1930.[2] The Holiday effect was documented as early as 1934 according to Thaler (1987a).[3] Since then much research has been made in many countries (e.g., Tong, 2000, Jaffe and Westerfield, 1985, Gultekin and Gultekin, 1983) and regarding several assets (e.g., Flannery and Protopapadakis, 1988, with t-bonds and Ka, 1986, with gold futures). In many cases significant regularities were found.

Next, the most common results will be presented followed by a list of possible explanations. Some of these hypotheses, here presented without criticisms, are certainly more robust than others but none was shown empirically to be totally satisfactory. Additionally, some studies may suffer from methodological errors (Connolly, 1989) and we must be aware that this subject is prone to data mining. Clearly, spurious patterns might be found if many are tested. If spurious, these patterns will be strong within the sample but will disappear when out of the sample. Dimson and Marsh (1999) argued that the “anomalies”, in general, disappear after they are discovered. This is consistent with an investor learning hypothesis but could be simply a manifestation of the “anomalies” fading away out of the sample.

2.1 Day-of-the-week effect[4]

Most of the studies found low Monday returns (often negative and significant) and positive Friday returns, i.e., weeks tended to open weak and end strong. Interestingly, Australia and some markets in Asia showed low Tuesday returns (e.g., Jaffe and Westerfield, 1985). The most recent studies in the U.S. (Pettengil, 2003) now agree that this effect is essentially a small stock “anomaly”.[5]

Some explanations proposed for these effects are risk-based, i.e., risk may vary throughout the week, but others are related to the microstructure of the markets or to the trading behaviour of market participants. For instance, Keim and Stambaugh (1984) suggest that the frequency at which transactions are made at the bid or at the ask during the week could contribute to Day-of-the-week effects in the United States (U.S.). Settlement procedures could help create this pattern. These could make investors in certain days of the week unwilling to buy at the same price levels as in other days because they do not get the two days of extra credit granted by the weekend (e.g., Lakonishok and Levi, 1982).

In addition, there might be a pattern of information flows (macro or company specific). For instance, firms may announce bad or “shocking” news more frequently on Friday after the close of the session to allow investors to assimilate the information or there might be a pattern in the release of analysts buy/sell recommendations (e.g., Damodaran, 1989, Penman, 1987, Steeley, 2001) or in the ex-dividend dates across the week (e.g., Lakonishok and Smidt, 1988).

Concerning trading activity, the Information Processing hypothesis says that individual investors could be more active selling after their weekend financial analysis and planning (e.g., Osborne, 1962, Miller, 1988, Wang and Walker, 2000) but institutional traders may be less active, for instance, because they make their planning on Monday (e.g., Kamara, 1997, and Lakonishok and Maberly, 1990). The behaviour of short-sellers, closing their positions on Fridays and reopening them on Mondays, and the “Blue Monday” hypothesis stating that investors are less optimistic on Mondays and hence are less willing to buy and/or more willing to sell assets (e.g., Rystrom and Benson, 1989) are additional hypotheses.

2.2 January effect

January returns are usually positive and often significantly higher than other months. These could also be explained by variations in risk or risk premia throughout the year (e.g., Rogalski and Tinic, 1986, Kramer, 1994, and Garret, Kamstra and Kramer, 2005).

In addition, year-end events are offered as possible explanations. The Liquidity hypothesis is advanced because in January due to extra holiday payments, holiday gifts, and annual bonuses there is an increase in cash-flows invested in the stock market directly by individual investors or through mutual funds and pension funds. Investment decisions also tend to be made in January so there is a buying pressure during this month (e.g., Ogden, 1990). January is also a month during which much important information about companies is released (Rozeff and Kinney, 1976).

It also coincides, often, with a new fiscal and accounting year. Therefore, the Tax-loss Selling

[2]References are made to Persons (1919) and Kelly (1930), respectively.

[3]Thaler (1987a) cites the work of Fields (1934).

[4]A good source for the Day-of-the-week effect is the review by Pettengill (2003). Partial reviews are also made in Jacobs and Levy (1988), Thaler (1987a) and Thaler (1987b).

[5]The interesting shift in the U.S. could be caused by arbitragers, able to exploit the “anomaly” only with large stocks (Kamara, 1997). Obviously, because of time zone differences, the Tuesday effect in Asia could be a consequence of the Monday effect in the U.S. since it affects countries with markets closed when the U.S. and European markets are open.

hypothesis says that loser stocks may be sold at the end of the year (to take advantage of capital losses tax benefits), and that this capital might be reinvested only in January or, at least, the selling pressure decreases in January (e.g., Reinganum, 1983).

The Window Dressing hypothesis says that in order to benefit their end of year portfolio evaluation (to some extent based on their holdings at year end) managers "clean" their portfolios selling risky and small-cap stocks and buying blue-chips and less risky stocks during December (making the portfolios appear more conservative). On January, the process is reversed and the buying pressure on small-caps and risky stocks increase (e.g., Haugen and Lakonishok, 1988). Similar actions could be taken if portfolio managers, after achieving a good performance, "park" their money investing in their benchmarks during the rest of the year.

2.3 Turn-of-the-month effect

Returns tend to be much higher around the turn-of-the-month than in other days. One of the explanations proposed for this "anomaly" is also risk-based (risk could vary during the month and be higher during the turn-of-the-month). The Liquidity hypothesis is again plausible if salaries, dividends and interest are received mostly at the end of the month increasing the buying pressure in this period (e.g., Ogden, 1990). There might also be some patterns of information flows, for instance, positive earnings announcements could be clustered around the beginning of the month.

2.4 Holiday effect

The common result is that the pre-holiday stock return is significantly higher than returns in regular days. Most of the time, the post-holiday return is also higher than a regular day return. An explanation for these results include the possibility that short-sellers cover their positions before the holiday for peace of mind (but the holders of long positions do not) and that holiday euphoria builds buying pressure (e.g., Frieder and Subrahmanyam, 2004).

2.5 Tests in the Portuguese stock market

The discovery of regularities in the Portuguese stock market has not received much attention so far. To our knowledge there are just three papers covering the subject with some detail: Gama (1998), Marcelo and Quirós (2000) and Balbina and Martins (2002).[6]

The Weekday effect was investigated by Gama (1998) using two tests: an ANOVA F-Test for the equality of means between weekdays and the Kruskall-Wallis test. He did not find significant differences between weekdays. The only exception was the Kruskall-Wallis test that detected a significant difference (p-value less than 5%) between the means for one sub-period (1993-96) but only with the PSI-Geral index.

Marcelo and Quirós (2000) start their analysis of the Weekday effect with the OLS regression with dummies. Using the GMM (Generalized Method of Moments) they could reject the equality between the overnight return from Thursday to Friday and the other overnight returns. Using a GARCH model they found a seasonality pattern affecting the overnight returns, too.

Balbina and Martins (2002) studied the Weekday effect with the standard OLS regression with dummies but with four additional explanatory variables. They included the first three lags of the dependent variable and one additional dummy for the Tuesdays until May, 1989.[7] They excluded all observations immediately after or before holidays. They tested for the equality of weekday coefficients and this hypothesis could not be rejected. The rejection was stronger for the second half of their sample.

A similar regression was made in order to test the Monthly effect. Again, there were no significant differences between monthly coefficients. They found just one significant and positive coefficient (p-value less than 1%) for the January dummy during one sub-period.

The approach to test the Turn-of-the-month effect was different. Balbina and Martins (2002) present only summary statistics for day *n-4* till *n+4* (being *n-1* and *n+1* respectively the last and the first trading days of the month) and test which means are statistically different from zero. Day *n+3* (5% level), *n-3* and *n-1* (10% level), are the only statistically significant. Gama (1998) considers *n-1*, *n+1*, *n+2* and *n+3* the trading days belonging to the Turn-of-the month. Then he computes a daily average of these days and compares it to the average of the other days not belonging to this "window". The return is higher for the Turn-of-the-month days but neither a t-test for the equality of means nor the Mann-Whitney test are able to reject the equality of these two groups.

Finally, both study the Holiday effect. Balbina and Martins (2002) do not test the differences between pre-holiday, post holiday and regular days but they note that the mean return in pre-holiday days is 23 times higher than in regular days. Gama (1998), working with shorter samples, found smaller differences and, according to the t-test and the Mann-Whitney test, none were significant.

[6] A version of the Balbina and Martins paper was later published in "Boletim Económico do Banco de Portugal", December 2002.

[7] The Portuguese stock market was closed on Mondays before this date.

3. DATA

The PSI-Geral (or BVL-Geral) and the PSI20-TR (Total Return) series were collected from the Euronext Lisbon (Dathis database). These indexes are total return indexes reflecting both price appreciation and the dividends paid by its constituents (the indexes are corrected by the gross dividend in the ex-dividend date).

PSI-Geral is a capitalization-weighted index that includes all stocks listed in the Main Market of Euronext Lisbon. The PSI20-TR index is also a capitalization-weighted index (where the weights are free-float adjusted and have a "cap") and its constituents are the 20 most important stocks listed in the market.

The PSI-Geral series started in January 5, 1988 with a value of 1000. However, the Portuguese stock market was closed on Mondays until April, 1989. Therefore our sample begins in the first trading day of May, 1989 ending on December 31, 2008. The PSI20-TR series starts on December 31, 1992 with a value of 3000. We use the complete series until December 31, 2008. Log returns were computed as $\log(price_t/price_{t-1})$ for daily frequencies using close prices.

Summary statistics are presented in Table 1 revealing non-normal return distributions (the Jarque-Bera statistic is significant at the 1% level) especially because of the high kurtosis coefficients. The distributions are negatively skewed but this feature is less obvious and closer analysis may fail to reject symmetry (Silva, 2008).

Table 1: Summary statistics (PSI-Geral and PSI20-TR)

	PSI-Geral	PSI20-TR
Mean	0,0211%	0,0302%
Median	0,0202%	0,0500%
Maximum	9,744%	9,710%
Minimum	-10,814%	-10,380%
Std. Deviation	0,970%	1,087%
Skewness	-0,656**	-0,549**
Kurtosis	19,131**	13,611**
Jarque-Bera	53642**	19015**
Observations	4915	4010
ADF test (returns)	-11,03**	-10,41**

PSI-Geral series starting in May 2, 1989. PSI20-TR starting in December 31, 1992.
* significant at 5% level. ** significant at 1% level.
The t-test for the mean follows a t distribution with *n-1* degrees of freedom. Under normality and for large sample sizes skewness follows N(0, 6/*N*) and excess kurtosis (computed as the kurtosis coefficient above minus three) follows N(0, 24/*N*). All tests were two-tailed. The ADF test reported is the Augmented Dickey-Fuller performed with an intercept and an optimal lag structure according to the Akaike Information Criteria.

The PSI-Geral index will be used as the main testing index because it has a longer time series. The PSI20-TR index will be used as an alternative index for double checking our conclusions.

4. EMPIRICAL RESULTS

4.1 Day-of-the-week effect

The results in Table 2 show that all weekdays have positive average returns but Monday has the lowest mean return and the highest standard deviation while Friday has the highest mean return (statistically different from zero) and the lowest standard deviation. These results are consistent with most of the international and the Portuguese studies. This pattern is replicated in the first sub-period but it is not stable. In the second sub-period Tuesday has the best weekday return and Thursday has the worst. In the third sub-period Wednesday is the best and Thursday is, again, the worst weekday. Friday has a positive mean return in all sub-periods.

These differences between weekdays are not significant according to the F-test or the non-parametric Kruskal-Wallis test which is, obviously, more robust to the violation of the normality assumption. The null hypothesis of equality of means is never rejected and, consequently, the existence of any weekday effect is not supported.

The classic OLS regression to detect weekday effects includes five dummy variables as independent variables. We added as a sixth variable the lagged return on the index to help remove autocorrelation.[8] The model becomes:

$$R_t = \beta_1 D_{1t} + \beta_2 D_{2t} + \beta_3 D_{3t} + \beta_4 D_{4t} + \beta_5 D_{5t} + \beta_6 R_{t-1} + \varepsilon_t \quad \ldots (1)$$

where

R_t is the index return in period t, ε_t is the error term, D_{1t} is the dummy variable for Mondays (D_{1t} = 1 if the observation t falls on a Monday and 0 otherwise), D_{2t} for Tuesdays, etc. Our goal is to test the following null hypothesis:

$$H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 \quad \ldots (2)$$

The results in Table 3 are not very supportive of a Weekday effect. The Wald tests reject the hypothesis of equal weekday coefficients only for sub-period 1. Apart from the lagged variable for the index return the

[8] We repeated this regression including additional lagged values for the index. However, the results (not reported) showed that these additional coefficients were not statistically significant. In any case Newey-West standard errors will be used to compute standard errors.

only significant coefficient belongs to Friday for the full sample.

When we run the same regression excluding the observations before and after holidays all but one coefficient (Friday) decline which is symptomatic of the good performance around holidays.[9] The weakest (most negative) Weekday effect continues to be the Monday return (non-significant) and the strongest coefficient continues to be the Friday return (with a p-value increasing from 4,3% to 5,3%).

Table 4 shows the distribution of extreme returns per day of the week where we see that the extreme negative returns occur more frequently on Mondays. Positive extreme returns are concentrated in the first part of the week but are observed mainly on Tuesdays. Later we will study the impact of outliers on our results.

4.2 Monthly effects

Table 5 gives the first insights into the monthly effects we may expect. The best month is February which is positive for all sub-periods and robust to the exclusion of pre and post-holidays and Fridays. The second best month is January and the third is December. However, we should note that January returns are negative in the first and third sub-periods and that the good average performance in January is due solely to the good performance in the second sub-period.[10] December has positive average returns in all sub-periods but it is sensitive to the exclusion of holidays.[11] September and June (negative in all sub-periods) are the worst months.

Considering the full sample, Table 5 shows that there are two significant (statistically different from zero) monthly means (both positive): February (1% level) and December (5% level). The equality of the twelve monthly coefficients, nonetheless, cannot be rejected for the full sample.

Our regression to detect monthly effects will now include 12 dummy variables as independent variables. We added, again, the lagged return on the index so the model becomes:

$$R_t = \sum_{i=1}^{12} \beta_i D_{it} + \beta_{13} R_{t-1} + \varepsilon_t \qquad \text{... (3)}$$

where

R_t is the index return in period (day) t, ε_t is the error term, D_{1t} is the dummy variable for January (D_{1t} = 1 if the observation t belongs to January and 0 otherwise), D_{2t} for February, and so on. Our goal is now to test the following null hypothesis:

$$H_0 : \beta_1 = \beta_2 = ... = \beta_{12} \qquad \text{... (4)}$$

Table 6 shows that we are unable to reject it. The February and December coefficients are significant in the full sample. February is significant in the first sub-period and January and December are significant in the second. In the third sub-period, however, only April (with an exceptional 2007 and 2008 performance) is significant.

Despite the above average returns around the turn-of-the year we must acknowledge that the results of the equality tests, the low explicative power of the regressions but, especially, the instability of the estimated coefficients over the sample period are evidence against the existence of monthly effects in the stock market.

4.3 Turn-of-the-month effect

When we analyse Figure 1 we find reasons to deepen the study of the Turn-of-the-month effect. Actually, we see positive returns from the trading day -1 (the last day of a month) until the fifth trading day of a month, all above average with the exception of day 4.

This sequence of 6 days has an average return of 0,091% against -0,007% on the other days (Table 7, panel A). If we exclude pre-holidays the averages decrease to 0,082% and -0,011%, respectively. These differences are both significant according to the t-test for the equality of means and the non-parametric Mann-Whitney U-test. Methodologically, the choice of 6 days could be considered excessive. For instance, Gama (1998) chooses only four turn-of-the-month days (*n-1*, *n+1*, *n+2* and *n+3*). Accordingly, we repeated the calculations considering only four days and the conclusions were exactly the same (Table 7, panel B).

[9]The full table is available upon request.

[10]1997, 1998 and 2001 had particularly good January returns.

[11]The mean return in December becomes 0.0223% when we remove pre and post-holidays (81 out of 379 observations).

Table 2: Return statistics by day of the week

		Obs.	Mean	Std. Dev.	Max.	Min.	Skewness	Kurtosis
Full sample	**Monday**	978	0,0023%	1,12%	9,74%	-10,81%	-1,59	28,96
(May 1989 – Dec 2008)	**Tuesday**	982	0,0327%	0,93%	5,95%	-5,95%	-0,05	10,19
	Wednesday	998	0,0030%	0,93%	6,41%	-4,56%	0,18	10,38
K-W H: 2,836	**Thursday**	978	0,0109%	0,95%	7,57%	-8,34%	-0,81	17,13
F-Stat: 0,5719	**Friday**	979	0,0568%*	0,89%	7,39%	-6,17%	-0,18	13,89
	All	4915	0,0211%	0,97%	9,74%	-10,81%	-0,66	19,13
Sub-period 1	**Monday**	329	-0,0384%	0,97%	4,85%	-10,81%	-4,54	54,43
(May 1989 – Dec 1995)	**Tuesday**	326	-0,0024%	0,66%	3,58%	-2,51%	0,94	9,67
	Wednesday	334	-0,0321%	0,60%	2,55%	-3,66%	-0,49	10,08
K-W H: 6,868	**Thursday**	327	0,0612%	0,78%	7,57%	-1,75%	3,37	30,52
F-Stat: 1,5380	**Friday**	331	0,0660%*	0,59%	3,82%	-2,06%	1,24	11,37
	All	1647	0,0107%	0,73%	7,57%	-10,81%	-1,08	44,33
Sub-period 2	**Monday**	319	0,0664%	1,12%	3,67%	-6,56%	-0,79	9,34
(Jan 1996 – June 2002)	**Tuesday**	321	0,0867%	1,13%	4,44%	-5,95%	-0,56	7,38
	Wednesday	327	0,0042%	1,12%	6,41%	-4,19%	0,51	7,70
K-W H: 2,038	**Thursday**	319	0,0018%	1,14%	3,70%	-8,34%	-1,73	13,76
F-Stat: 0,4250	**Friday**	319	0,0718%	1,01%	3,79%	-4,06%	-0,20	5,44
	All	1605	0,0461%	1,10%	6,41%	-8,34%	-0,58	9,05
Sub-period 3	**Monday**	330	-0,0192%	1,27%	9,74%	-10,65%	-0,77	29,23
(July 2002 – Dec 2008)	**Tuesday**	335	0,0151%	0,95%	5,95%	-4,52%	0,33	11,69
	Wednesday	337	0,0367%	0,99%	6,38%	-4,56%	-0,24	10,28
K-W H: 1,927	**Thursday**	332	-0,0298%	0,91%	3,27%	-5,27%	-1,55	11,37
F-Stat: 0,2865	**Friday**	329	0,0329%	1,02%	7,39%	-6,17%	-0,39	18,22
	All	1663	0,0073%	1,04%	9,74%	-10,65%	-0,56	21,24

* significant at 5% level. ** significant at 1% level. The t-test for the mean follows a *t* distribution with *N-1* degrees of freedom where *N* is the total number of observations. The F-Statistic reported tests the equality of means across weekdays. The F-statistic has an F-distribution with *G-1* numerator degrees of freedom and *N-G* denominator degrees of freedom where *G* is the number of subgroups tested. Equal variances were assumed since the Levene's test could not reject the null hypothesis of equal variances. The Kruskall-Wallis H test (K-W H) follows a chi-squared distribution with *G-1* degrees of freedom.

Table 3: Weekday effects – Regression results

	Full sample		Sub-period 1		Sub-period 2		Sub-period 3	
Variable	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Monday	-0,000078	-0,230	-0,000607	-1,260	0,000506	0,861	-0,000210	-0,317
Tuesday	0,000321	1,096	0,000098	0,269	0,000774	1,284	0,000161	0,307
Wednesday	-0,000026	-0,089	-0,000337	-1,111	-0,000117	-0,187	0,000361	0,653
Thursday	0,000102	0,339	0,000698	1,769	0,000023	0,036	-0,000322	-0,667
Friday	0,000566*	2,022	0,000480	1,667	0,000749	1,319	0,000348	0,630
R_{t-1}	0,152065**	5,616	0,319088**	5,473	0,165346**	4,052	0,054222	1,354
Adj, R-Squared	0,0226		0,1054		0,0283		0,0036	
F-statistic	0,884		2,682*		0,488		0,397	
Chi-sq. stat.	3,539		10,727*		1,953		1,59	
Observations	4915		1647		1605		1663	

*significant at 5% level, ** significant at 1% level. The F and the chi-squared statistics reported test the null hypothesis $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5$. Newey-West heteroskedasticity and autocorrelation consistent standard errors were used to compute t-statistics.

Table 4: Occurrence of extreme outliers per weekday

	R_i < - 4%	R_i < - 3%	R_i > 2,5%	R_i > 3,5%
Monday	7	12	13	4
Tuesday	4	9	16	5
Wednesday	2	10	11	3
Thursday	5	11	9	3
Friday	3	7	8	4
All	21	49	57	19

Table 5: Daily returns per month

	Full sample			Sub-period 1			Sub-period 2			Sub-period 3		
	Obs.	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**
January	409	0,09%	1,02%	129	-0,04%	0,91%	150	0,30%**	1,10%	130	-0,03%	1,00%
February	370	0,14%**	0,82%	113	0,20%**	0,63%	136	0,15%	0,91%	121	0,07%	0,87%
March	409	0,01%	0,88%	131	0,03%	0,54%	149	0,00%	1,07%	129	0,02%	0,92%
April	369	0,05%	0,88%	114	0,00%	0,44%	135	0,02%	1,28%	120	0,14%*	0,61%
May	425	0,00%	0,83%	148	0,00%	0,71%	148	-0,01%	1,05%	129	0,03%	0,64%
June	400	-0,07%	0,82%	135	-0,08%	0,66%	136	-0,06%	0,98%	129	-0,07%	0,78%
July	441	0,00%	0,79%	153	0,06%	0,46%	134	0,06%	0,81%	154	-0,11%	0,99%
August	434	0,00%	0,96%	152	0,13%	0,93%	128	-0,20%*	1,07%	154	0,03%	0,87%
September	427	-0,08%	1,13%	149	-0,02%	0,84%	128	-0,09%	1,30%	150	-0,13%	1,24%
October	434	0,00%	1,55%	148	-0,06%	1,17%	130	0,13%	1,55%	156	-0,04%	1,84%
November	418	0,05%	0,86%	146	-0,08%*	0,39%	124	0,10%	0,91%	148	0,14%	1,11%
December	379	0,08%*	0,73%	129	0,02%	0,55%	107	0,18%*	0,92%	143	0,07%	0,70%
	F-Stat: 1,69 (0,07)			F-Stat: 1,728 (0,0619)			F-Stat: 2,01 (0,0242)			F-Stat: 1,00 (0,44)		
	K-W H: 19,103 (0,059)			K-W H: 35,832 (0,000)			K-W H: 20,01 (0,045)			K-W H: 12,042 (0,361)		

* significant at 5% level, ** significant at 1% level. The t-test for the mean follows a *t* distribution with *N-1* degrees of freedom where *N* is the total number of observations. The F-Statistic reported tests the equality of means across months. The F-statistic has an F-distribution with *G-1* numerator degrees of freedom and *N-G* denominator degrees of freedom where *G* is the number of subgroups tested. Equal variances were assumed since the Levene’s test could not reject the null hypothesis of equal variances. The Kruskall-Wallis H test (K-W H) follows a chi-squared distribution with *G-1* degrees of freedom. P-values are shown in brackets.

Table 6: Monthly effects – Regression results

	Full sample		Sub-period 1		Sub-period 2		Sub-period 3	
Variable	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
January	0,000719	1,315	-0,000270	-0,407	0,002455**	2,900	-0,000293	-0,263
February	0,001173*	2,355	0,001400*	2,293	0,001262	1,346	0,000658	0,776
March	0,000122	0,284	0,000186	0,485	-0,000028	-0,031	0,000181	0,239
April	0,000460	1,180	0,000043	0,118	0,000164	0,184	0,001335*	2,308
May	-0,000026	-0,063	-0,000125	-0,207	-0,000164	-0,228	0,000247	0,339
June	-0,000577	-1,327	-0,000513	-1,139	-0,000459	-0,537	-0,000651	-0,751
July	-0,000009	-0,025	0,000370	0,926	0,000466	0,546	-0,001004	-1,623
August	-0,000007	-0,013	0,000992	1,245	-0,001779	-1,816	0,000337	0,554
September	-0,000723	-1,220	-0,000311	-0,492	-0,000739	-0,538	-0,001259	-1,410
October	0,000081	0,127	-0,000425	-0,669	0,001168	0,914	-0,000328	-0,234
November	0,000388	1,084	-0,000539	-1,692	0,000728	1,023	0,001309	1,677
December	0,000740*	2,387	0,000186	0,513	0,001615*	2,081	0,000634	1,309
R_{t-1}	0,148429**	5,461	0,310015**	5,282	0,153863**	3,787	0,047291	1,189
Adj, R-Squared	0,0233		0,1003		0,0298		0,0017	
F-Statistic	1,31		1,16		1,59		1,32	
Chi-Sq. Stat.	14,44		12,78		17,53		14,48	
Observations	4915		1647		1605		1663	

*significant at 5% level, ** significant at 1% level. The F and the chi-squared statistics reported test the null hypothesis $\beta_1 = \beta_2 = \ldots = \beta_{12}$. Newey-West heteroskedasticity and autocorrelation consistent standard errors were used to compute t-statistics (Newey and West, 1987).

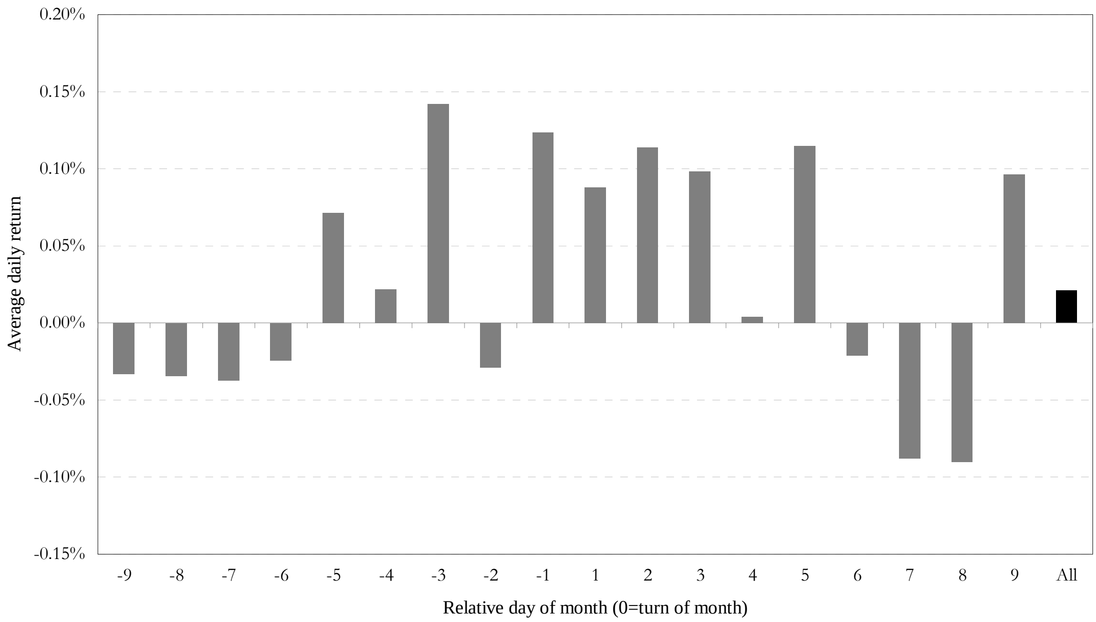

Figure 1: Average returns per trading day of the month

Table 7: Turn-of-the-month statistics

A: 6-Day Window							
	Full sample				*Sub-period 1*	*Sub-period 2*	*Sub-period 3*
	Mean	**Std. Dev.**	**Obs.**	**Difference**	**Difference**	**Difference**	**Difference**
Turn-of-the-month days	0,091%**	0,980%	1416				
	(3,474)			**0,0975%**	**0,036%**	**0,194%**	**0,064%**
Other days	-0,007%	0,900%	3499	t-test: 3,196**	0,904	3,210**	1,135
	(-0,430)			M-W U test: 3,062**	0,159	3,250**	1,706
	Full sample - Excluding days before holidays						
Turn-of-the-month days	0,082%**	0,996%	1331				
	(3,014)			**0,0932%**	**0,029%**	**0,195%**	**0,059%**
Other days	-0,011%	0,971%	3416	t-test: 2,949**	0,701	3,091**	1,035
	(-0,656)			M-W U test: 2,702**	0,208	3,066**	1,571
B: 4-Day Window	*Full sample*						
Turn-of-the-month days	0,106%**	0,966%	944				
	(3,372)			**0,1051%**	**0,057%**	**0,159%**	**0,100%**
Other days	0,001%	0,969%	3971	t-test: 2,997**	1,252	2,284*	1,541
	(0,058)			M-W U test: 3,188**	0,510	2,900**	1,820
	Full sample - Excluding days before holidays						
Turn-of-the-month days	0,095%**	0,977%	876				
	(2,870)			**0,0982%**	**0,050%**	**0,152%**	**0,094%**
Other days	-0,003%	0,971%	3871	t-test: 2,682**	1,040	2,075*	1,416
	(-0,183)			M-W U test: 2,770**	0,143	2,640**	1,649

* significant at 5% level, ** significant at 1% level. The first t-statistic tests if the mean is significantly different from zero. The second is an independent samples t-test for the equality of means (equal variances assumed since the Levene’s test could not reject the null hypothesis of equality of variances). The M-W U test reports the statistic for the normal approximation of the Wilcoxon/Mann-Whitney U-test.

4.4 Holiday effect

The discussion of the Holiday effect has begun in the previous sections but here additional results will be provided. Table 8 shows that there were 168 weekdays when the stock market was closed.[12] The average return around these days was 0,186% (before) and 0,137% (after). This should be compared with the overall mean of 0,0211% (or 0,011% excluding pre and post-holidays).[13] The pre-holiday standard deviation is also lower than regular days or post-holidays. The tests reject the equality of means between pre-holiday returns and other days. On the contrary, they are unable to reject the equality between post-holiday and other days' returns.

The last columns of Table 8 also show that the Pre-holiday effect is consistently strong across sub-periods contrary to the Post-holiday effect that shows strong average returns in two sub-periods but has negative returns in the first part of the sample period.

Table 9 shows the reasons for the closure of the stock market and statistics per type of holiday. Only 5 holidays (out of 15) have negative returns (averaging the day before and after) and are below our full sample mean return.

An important change occurred in the last years of our sample. The Portuguese stock market became more integrated with the other European markets and in 2002 became part of the Euronext group. As a result, the number of holidays when the market is closed decreased substantially. For instance, during 2008 the market was closed during just six full days: New Year's Day, Christmas Day/Boxing Day, Good Friday/Easter Monday and Worker's day.

5. ROBUSTNESS CHECKS

We feel that the evidence presented so far would be fragile without further checks. The interaction of different patterns may confound the statistical tests. Besides, outliers or methodological weaknesses may influence our results. The choice of the index could be a sensitive decision. In this section we try to address these issues.

5.1 Interaction of effects

So far we have found two weak effects (Friday and the Turn-of-the-year effects) and two significant effects (the Turn-of-the-month and the Holiday effects). We will test now if these patterns are autonomous in relation to each other, i.e., if their significance is robust to the simultaneous consideration of the other regularities. The results are presented in Table 10.

To begin disentangling the simultaneous calendar effects first we estimated Model 1 that shows, again, that the post-holiday effect is not significant. So, our base case will be model 2 with the pre-holiday dummy variable and the lagged dependent variable. In model 3, after adding the five weekday dummy variables we see that the pre-holiday coefficient is still highly significant. The coefficient for Friday was the highest (p-value: 7,19%) so we decided to remove the other variables and re-estimate the model (model 4). The results are almost unchanged. This relative independence of effects could be expected after the analysis of Table 11 that shows that there were not many pre-holidays in our sample falling on a Friday.

In model 5 we add dummy variables for January, February and December. There we see that only February complies with the 5% significance level. The Friday coefficient in models 5 and 6 (where we remove January and December) falls and becomes non-significant. This happens, as well, when we consider the Turn-of-the-month dummy (4-day window) instead of the February dummy (model 7). This means that the Friday effect is not robust and disappears when we consider other regularities. The final model (8) considers the lagged dependent variable, the Pre-holiday, February and the Turn-of-the-month dummies. The results support the contention that these are autonomous effects. Nevertheless, the significance of the February coefficient (p-value: 5,1%) is still questionable.

5.2 Alternative indexes

It is important to know if these results are influenced by the index choice. Therefore, we estimated model 8 using the PSI20-TR index which has a shorter sample period. The comparison is made in Table 10. (Model 8a) where we see that the February coefficient is no longer significant. Running the same regression with the PSI-Geral for the same sample period (Model 8b) we can conclude that the shortening of the sample period and not the choice of index caused the drop in significance of the February coefficient.

[12] When the stock market was closed successive days due to the same festivity this was considered a single holiday. For instance, Good Friday and Easter Monday or Christmas Day and Boxing Day were considered single holidays. Holidays when the market was not closed during the full day were not considered.

[13] It is also interesting to compare these numbers with the average daily returns on Fridays (0,0568%), February (0,136%) and the Turn-of-the-month days (0,106%, considering the 4-day window).

Table 8: Holiday effect statistics

Day	Obs.	Mean	Std. Dev.	Difference in means	t-test	Mann-W.	% Positive	Sub-period 1	Sub-period 2	Sub-period 3
Before holiday	168	0,186%**	0,628%	+0,176%	2,25*	2,48*	59,5%	0,031%	0,373%	0,125%
After holiday	168	0,137%	1,074%	+0,127%	1,58	0,053	48,8%	-0,057%	0,271%	0,346%
Other days	4581	0,011%	0,975%	--	--	--	51,1%	0,012%	0,019%	0,001%

*significant at 5% level, ** significant at 1% level. The t-test reports the results of comparing the means between "before holidays" and "non before holidays" (first line) and "post-holidays" and "non post-holidays" (second line). The same groups are compared in the "Mann-W," column which reports the statistic for the normal approximation of the Wilcoxon/Mann-Whitney U-test. "% Positive" shows the percentage of positive observations within the group. The last columns present mean returns per sub-period.

Table 9: Returns per type of holiday

Holiday	Obs.	Before holiday	After holiday	Average
Worker's day (May, 1)	14	0,46%	0,66%	0,56%
Immaculate Conception (December, 8)	9	0,24%	0,59%	0,42%
St, Anthony's day (June, 13)	5	0,26%	0,52%	0,39%
New Year's day (January, 1)	15	0,37%	0,25%	0,31%
Christmas (December, 25)	19	0,41%	0,16%	0,29%
All Saints' day (November, 1)	11	0,36%	0,16%	0,26%
Carnival (variable, February/March)	13	0,16%	0,28%	0,22%
Good Friday (variable, March/April)	19	0,15%	0,23%	0,19%
Republic day (October, 5)	10	0,38%	-0,05%	0,17%
All	*168*	*0,19%*	*0,14%*	*0,16%*
Liberation day (April, 25)	8	-0,09%	0,19%	0,05%
National day (June, 10)	6	-0,08%	0,02%	-0,03%
Assumption day (August, 15)	10	0,20%	-0,42%	-0,11%
Other *	9	0,02%	-0,26%	-0,12%
Independence day (December, 1)	9	-0,42%	0,06%	-0,18%
Corpus Christi (variable, May/June)	11	-0,18%	-0,55%	-0,37%

*Includes other holidays, different successive holidays, and other weekdays when the market was closed. The last column averages the pre and post-holiday mean returns.

Table 10 – Models to test the interaction of calendar effects

	Full sample - PSI-Geral								PSI20-TR	PSI-Geral	PSI-Geral
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 8a	Model 8b	Model 8 - Trimmed
Before holiday	0,00192**	0,00194**	0,00185**	0,00184**	0,00168**	0,00179**	0,00157**	0,00157**	0,00214**	0,00217**	0,00152**
	(3,929)	(3,945)	(3,636)	(3,728)	(3,353)	(3,615)	(3,154)	(3,169)	(3,229)	(3,550)	(3,138)
After holiday	0,00107										
	(1,293)										
Monday			-0,00014								
			(-0,421)								
Tuesday			0,00028								
			(0,946)								
Wednesday			-0,00010								
			(-0,350)								
Thursday			0,00003								
			(0,099)								
Friday			0,00051	0,00051	0,00034	0,00043	0,00037				
			(1,800)	(1,805)	(1,183)	(1,520)	(1,271)				
December					0,00048						
					(1,518)						
January					0,00065						
					(1,183)						
February					0,00105*	0,00103*		0,00097	0,00083	0,00087	0,00083
					(2,103)	(2,060)		(1,953)	(1,370)	(1,585)	(1,773)
Turn-of-the-month							0,00075*	0,00074*	0,00097*	0,00084*	0,00072**
							(2,260)	(2,294)	(2,415)	(2,304)	(2,806)
R_{t-1}	0,15155**	0,15227**	0,15255**	0,15224**	0,15029**	0,15117**	0,15106**	0,15007**	0,13054**	0,12419**	0,17532**
	(5,558)	(5,582)	(5,609)	(5,586)	(5,522)	(5,549)	(5,558)	(5,522)	(4,838)	(4,368)	(8,962)
Adj. R-Squared	0,0240	0,0238	0,0236	0,0242	0,0249	0,0248	0,0250	0,0255	0,0200	0,0183	0,0352
F-Statistic	7,80**	15,57**	3,56**	9,23**	5,29**	7,36**	7,52**	8,13**	7,80**	8,78**	8,15**
Observations	4915	4915	4915	4915	4915	4915	4915	4915	4010	4010	4736

*significant at 5% level, ** significant at 1% level. The F statistics reported test the null hypothesis that all dummy coefficients are jointly zero. Newey-West heteroskedasticity and autocorrelation consistent standard errors were used to compute t-statistics (Newey and West, 1987).

Table 11: Pre-holidays by day-of-week

	Monday	Tuesday	Wednesday	Thursday	Friday
Pre-holiday falls on:	34	23	42	38	31
%	20,2%	13,7%	25,0%	22,6%	18,5%

5.3 Influence of outliers

To study the influence of outliers we removed 2% (98 observations) of the PSI-Geral returns symmetrically (1% in each tail of the distribution). Interestingly, none of the pre-holiday returns were removed. Four outliers belonged to February and 20 belonged to the four-day period that we defined as Turn-of-the-month. Therefore, we expect that, at least, the Holiday effect will remain strong.

Table 10 (last column) shows the results of our trimmed regression where we see that February is, again, non-significant contrary to the other coefficients that are not being influenced by outliers.

5.4 Stability of effects

By dividing the sample in three sub-periods we have been implicitly testing for the stability of these effects. In fact, if the regularities exist, they should be detected in sub-periods and also out of sample. Table 7, for instance, shows that for all sub-periods the average return difference between the Turn-of-the month days and regular days of the month is always positive (and significant in sub-period 2). That same conclusion was drawn for the pre-holiday effect from Table 8. This is indicative of the consistency of these effects over the time.

To further examine this issue we computed the recursive coefficients for the trimmed regression in Table 10.[14] In general, the coefficients increase as the sample increases stabilizing in the last part of the period but the Turn-of-the month coefficient is negative during the initial one-third of the sample.

6. Trading rules investment performance

Statistical significance does not necessarily imply economic significance. Therefore, we make a preliminary attempt to test three trading rules based on the calendar patterns that we found statistically significant. The first trading rule generates a buy signal immediately before a pre-holiday and a sell sign immediately before the end of the pre-holiday, i.e., the investor takes a long position in the index only during pre-holidays. The second trading rule explores the turn-of-the month pattern and generates a buy signal at the close of the day before the last trading day of the month and a sell sign at the close of the third trading day of the month. When the investor is not exposed to the market we assume that the investment is parked in a bank deposit earning the risk-free rate.[15] A third trading rule combines the previous two. First, the significant calendar patterns (Pre-holiday and Turn-of-the-month) are underlined in the calendar. Only then the buy and sell signals are determined. A buy signal is originated immediately before the beginning of the pattern or the sequence of patterns and a sell signal is triggered in the end of this pattern or this sequence. In any uninterrupted sequence of patterns the sell signals are delayed until the end of the sequence.

A buy-and-hold strategy and a risk-free investment are used for comparison purposes in Figure 2.

These preliminary results show the profit potential associated these strategies, although no attempt was made to adjust for transaction costs and taxation. The combined trading rule is the most profitable but we emphasize that the second best is the turn-of-the-month trading rule and only then the pre-holiday trading rule, penalized for its limited exposure to the market.

7. CONCLUSIONS

The Monday effect could not be found in the Portuguese stock market. Among the weekdays we can distinguish, at most, a superior Friday return. While this result is fairly consistent across sub-periods, it does not outlive the simultaneous consideration of the other calendar effects. This result is consistent with Gama (1998) and Balbina and Martins (2002). Interestingly, using one methodology (out of three) Marcelo and Quirós (2000), found a significantly higher Friday return. Analyzing both open and close values for the index (BVL30) they considered that this higher return appears during the non-trading overnight period between Thursday and Friday.

[14] Full results are available upon request.

[15] The risk-free rate is proxied by the interbank money market rate for daily deposits until December 31, 2002 and by the EONIA (Euro OverNight Index Average) after that day.

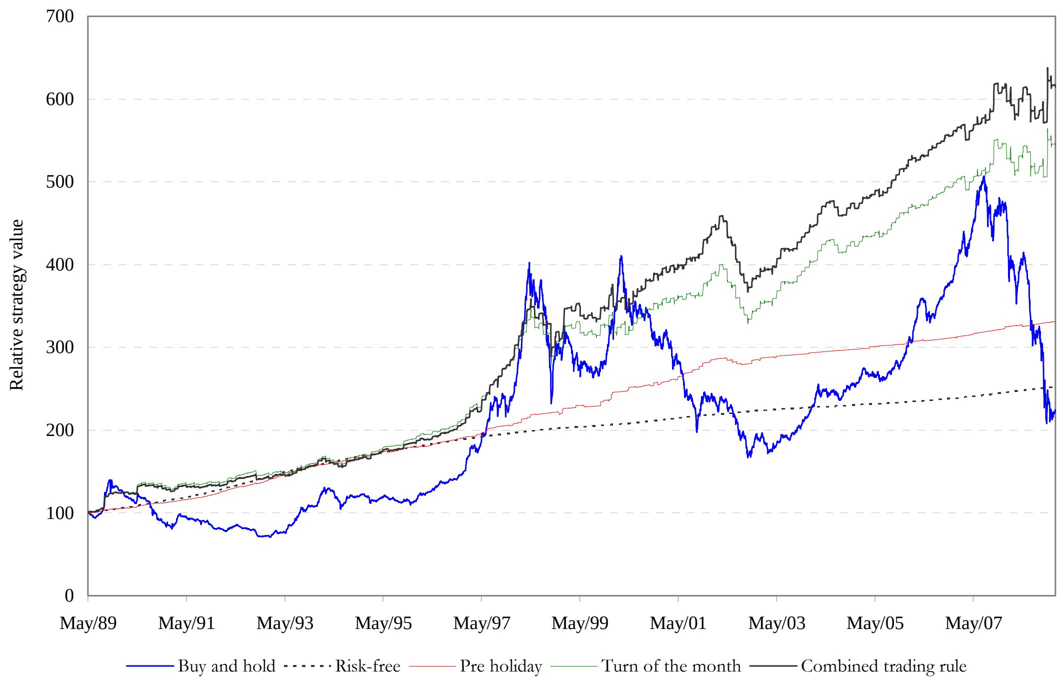

Figure 2: Investment strategies based in the calendar patterns

There is also a weak Turn-of-the-year effect since the three best mean monthly returns belong to December, January and February. Nonetheless, we are unable to assert that this effect is significant because the statistical evidence is too fragile due to the instability of the effect over time and the lack of independence in relation to the other calendar patterns. Balbina and Martins (2002) investigated this effect and reached the same conclusion for the Portuguese stock market.

Our results find some statistical support for the existence of the other calendar effects. First, we found superior returns on the days before holidays. Some evidence of this effect had been given by Balbina and Martins (2002) while Gama (1998) detected higher but not statistically significant returns on days before holidays.

We found evidence that returns were superior during the “window” including the last and first days of the month. This result contradicts the previous results of Balbina and Martins (2002) and Gama (1998) that did not find significant effects.

These positive findings were autonomous, not influenced by outliers or the choice of the market index and seem to be economically significant, too. The only concern about the robustness of our results is the stability of these effects. While it is expected that the regression coefficients would be unstable in the beginning of the sample, we see that, recursively, the turn-of-the-month coefficient only turns positive after 1994, almost five years after the beginning of the sample period. The holiday effect is statistically stronger and more stable. After an initial period the coefficient quickly becomes positive and the above average performance is fairly consistent across sub-periods. Unfortunately, nowadays it would not be easy to exploit this strong effect. Not many years ago the market would close about 11 days per year because of holidays. Now, stock exchanges remain open during most of the public holidays and the profit potential associated with this pattern is necessarily limited.

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