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Calendar Effects in Stock Markets: Critique of Previous Methodologies And Recent Evidence in European Countries [1]

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Calendar Effects in Stock Markets:
Critique of Previous Methodologies
And Recent Evidence in European Countries

Abstract

This paper examines day of the week and month of the year effects in seventeen European stock market indexes in the period 1994-2007. We discuss the shortcomings of model specifications and tests used in previous work, and propose a simpler specification, usable for detecting all types of calendar effects. Recognizing that returns are non-normally distributed, autocorrelated and that the residuals of linear regressions are variant over time, we use statically robust estimation methodologies, including bootstrapping and GARCH modeling. Although returns tend to be lower in the months of August and September, we do not find strong evidence of across-the-board calendar effects, as the most favorable evidence is only country-specific. Additionally, using rolling windows regressions, we find that the stronger country-specific calendar effects are not stable over the whole sample period, casting additional doubt on the economic significance of calendar effects. We conclude that our results are not immune to the critique that calendar effects may only be a "chimera" delivered by intensive data mining.

JEL codes: G10, G14, G15

Key words: Day-of-the-week effect; Month effect, Market efficiency, European stock markets

1. Introduction

Several empirical studies have studied the phenomena of calendar effects in stock markets, where returns tend to show higher (or lower) than average returns is specific calendar periods. The calendar effects that have attracted more interested, fueled by favorable evidence, are: (i) the weekend effect, where Monday returns tend to be lower than on other days of the week, and sometimes Friday returns are higher; and (ii) the January effect, revealed in the fact that daily returns tend to be higher in this month, than in other months of the year. Other calendar effects that have been studied include day of the month effects, where higher returns tend to be concentrated in specific periods of the month, and holiday effects, where we observe the behavior of returns after holidays (no trading days).

The study of calendar effects is relevant, in financial economics, because some types of calendar effects are inconsistent with the efficient market hypothesis. If the flow of information is continuous, and prices reflect all information, we would expect to find that Monday returns are around three times higher than other weekday returns, because there are three calendar days between the market closing of Friday, and the market closing of Monday. But even if we admit that the flow of information is negligible on weekends, Monday returns should at least be as high as other weekday returns. However, none of these two hypotheses is confirmed in the US market, nor in several other markets. Monday returns are in fact lower than other weekday returns. On the other hand, month effects are not necessarily inconsistent with market efficiency, because it is possible that the flow of information to the markets is specially concentrated in one, or some, of the months of the year. In any case, there is no strong evidence that January higher returns are caused by a relatively higher flux of good news, and so calendar effects remain at odds with both the hypothesis of: (i) market efficiency and (ii) rational behavior of investors. The study of calendar effects is also relevant for financial managers, financial counselors, market professionals and investors in general, and all those interested in developing profitable trading strategies.

This paper looks exclusively at day of the week effects and month of the year effects, in European stock markets. It makes several contributions to the literature on calendar effects in stock market returns. First, we discuss the shortcomings of previously used models for the detection of calendar effects, and we propose a simpler model specification that overcomes those shortcomings. Second, we recognize non-normality and autocorrelation in stock market returns, and time-dependent variance of the residuals of linear regressions, and apply appropriate statistical methodologies to tackle these problems, including the bootstrap approach and the GARCH model, adding statistical robustness to our results. Third, we examine the time-stability of the most significant calendar effects in the period under study. Fourth, we use observations from a set of seventeen countries of the same economic region, allowing us to conclude if calendar effects are across-the-board effects in that region or only country-specific effects. This is important to know, because some possible explanations for calendar effects, like psychological traits of investors, would imply across-the-board effects, while other explanations, like those related to fiscal motivations or market structure, allow for country-specific calendar effects. Five, we use data from recent years, from 1994 to 2007, on West and Central European stock markets, thus adding and updating international evidence on calendar effects.

The remainder of the paper is organized as follows. In section 2, we present some of the more relevant previous studies and results on day of the week effects and month of the year effects. In section 3, we present the data, including several descriptive statistics. In section 4, we discuss alternative model specifications and their shortcomings, and the different statistical methodologies we use for estimating the calendar effects. Section 5 contains the results of the model estimations and also includes an examination of the time-stability of the detected calendar effects. In Section 6, we present the conclusions and suggestions for further research.

2. Literature Review

Many researchers have studied the phenomenon of seasonalities in price movements in stock markets, related to specific calendar periods. These regularities are known as calendar effects. The most commonly studied calendar effects, which we also cover in the present study are: (i) the day of the week effect, and (ii) the month of the year effect. There are several studies which focus on other types of calendar effects, like the behavior of daily returns after holidays, or the behavior of returns in the first trading days of each month, but those are beyond the scope of this paper. In this section, we present a short review of previous works on day of the week and month of the year effects, and of the results they find.

2.1. The day of the week effect

Cross (1973) is among the group of authors that first studies a day of the week effect, namely, the weekend effect. He observes several US market indexes, without performing statistical tests, and finds that stocks have a negative return over the weekends. French (1980), Keim and Stambaugh (1984), Rogalski (1984), and Smirlock and Sarks (1986) examine the Standard & Poor's and the Dow Jones Index and conclude that Monday returns are on average negative. However, Rogalski (1984), using OLS regressions, F-tests and t-tests, observes that the Monday effect is negative but not statistically significant. In the nineties, Chang et al. (1993) and Kamara (1997) confirm the validity of the weekend effect.

Using the same approach as Rogalski (1984), other authors, including Jaffe and Westerfield (1985a, 1985b), Condoyanni et al. (1987) and Chang, et al. (1993), study non-US markets, including Japan, Singapore, Australia, Canada, UK, and other European countries, and find that Monday returns are on average negative and statistically significant. Other studies find a day of the week effect in different days. Brooks and Persand (2001) observe significant negative returns on Tuesdays in Thailand and Malaysia, and a significant Wednesday effect in Taiwan. Jaffe and Westerfield (1985a) and Dubois and Louvet (1996) confirm that daily returns in some Pacific countries tend to be negative on Tuesdays.

This apparent consensus is challenged by a set of more recent studies. Sullivan, Timmermann and White (2001) use a non traditional approach (a bootstrap procedure) and conclude that calendar effects no longer remain statistically significant. Rubinstein (2001), Mabberly and Waggoner (2000), Schwert (2001), Steeley (2001), Kohers et al. (2004) and Hui (2005) undertake international studies and show that this market anomaly is recently becoming weaker, particularly in developed markets. More recently, Chukwuogor-Ndu (2006) analyze the day of the week effect in stock market returns in fifteen European countries and finds corroborative evidence in only seven of those markets. He also finds significant negative returns on Tuesdays, in some of these countries. Basher and Sadorsky (2006), using different models for detecting the day of the week effect, conclude that a majority of the twenty one emerging stock markets they examine do not have such an effect, but some countries do exhibit strong day of the week effects, even after considering for conditional market risk. Overall, there is mixed evidence on day of the week effects, as more recent studies, using more advanced statistical procedures, have cast some doubt on the favorable evidence from the initial studies.

2.2. The month of the year effect

A month of the year effect exists if returns tend to be higher or lower in a specific month, when compared with the other months of the year. The most commonly reported month effect is the tendency for returns to be higher in January, although other month effects have also been reported. The first studies, by Rozeff and Kinney (1976), Dyl (1977) and Brown et al. (1983) analyze the US stock market and observe significant higher returns in January than in the other months of the year. Also, Gultekin and Gultekin (1983) study seventeen countries using both non-parametric and parametric tests, and conclude that January returns are significantly higher when compared with the other months, in thirteen of those countries.

Keim (1983) links the January effect to a small-firm effect, and a set of international studies find that small firms achieve larger rates of returns than larger firms, and that this is particularly evident in January (Aggarwal, Rao and Hiraki, 1990). Reinganum (1983) also finds that the January effect is largely due to the behavior of prices of small firms, and related to a tax-loss selling hypothesis as proposed by Brown, et al. (1983), who argues that selling pressure at the end of the tax year depresses price that rebound back in January. A study of the UK market by Menyah (1999) finds an April effect for small firms, besides a January effect for larger firms.

Ho (1990) examines twelve stock markets, including Australia, Japan, Korea, New Zealand, Singapore, Thailand, UK and US, and finds evidence corroborative of the January effect as he observes that average returns on January are higher than other months at a 95% level of confidence. More recently, Haugen and Jorion (1996), Tonchev and Kim (2004) and Rosenberg (2004) reach empirical findings similar to prior studies. In balance, the evidence of a January effect is mostly confirmatory, although the reasons why it exists are still under discussion.

3. Data

We collect from Reuters daily data on seventeen Western and Central European stock market indexes, for the period beginning in January, 1994 through to December, 2007. The countries and respective stock market indexes are, in alphabetical order: Austria (ATX), Denmark (OMXC20), Finland (OMXHPI), France (CAC40), Germany (DAX), Greece (ASE), Hungary (BUX), Iceland (OMXIPI), Ireland (ISEQ), Italy (MIBTEL), Netherlands (AEX), Norway (OSEAX), Poland (WIG), Portugal (PSI20), Spain (IBEX), Switzerland (SMI) and United Kingdom (FTSE).

For all indexes, daily returns are computed as:

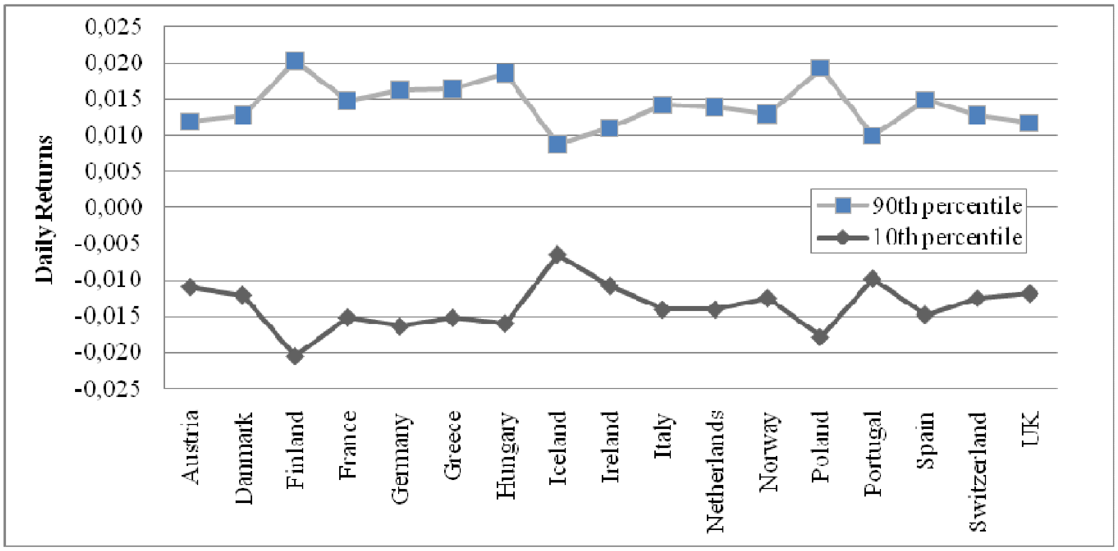
$$r_t = \ln\left(P_t / P_{t-1}\right) \tag{1}$$

Where r_t is the daily return of the stock market index and P_t is the stock index at date t. When the stock market is closed on a weekday, we do not compute the daily return both for that day and for the following weekday, this resulting in two missing observations. Thus all daily returns are computed with a lag of one calendar day, except Mondays, which have a lag of three calendar days. This results in an average of 3430 observations per country, with a maximum of 3595 observations for the United Kingdom and a minimum of 3279 observations for Poland. The descriptive statistics for daily returns of all seventeen stock market indexes are presented in Table 1.

INSERT TABLE 1

From Table 1, we find that the mean daily returns range between 0.016% in United Kingdom and 0.089% in Iceland. In that fourteen year period, the maximum daily returns have been registered in Finland (+14.6%), Hungary (13.6%) and the Netherlands (+ 9.5%), while the minimum daily returns happened in Hungary (-18.0%), Finland (-17.4%) and Poland (-11.3%). The standard error of the mean is lower in Iceland (0.0001313), Portugal (0.0001691) and the United Kingdom (0.0001751), suggestive of lower return volatility, and higher in Finland (0.0003283), Poland (0.0003026) and Hungary (0.0002907), a signal of relatively higher volatility. The 90th percentile daily return ranges from 0.87% in Iceland to 2.02% in Finland. The 10th percentile daily return ranges between -2.05% in Finland and -0.65% in Iceland. Figure 1 confirms, visually, that Finland, Hungary and Poland had wider ranges between the 10th and the 90th percentile, and the narrower ranges were in Iceland, Portugal and Ireland.

Figure 1
10th and 90th Percentiles of Daily Returns by Country (1994-2007)



In all countries, the distribution of returns is negatively skewed, which means that the left tail (negative returns) concentrates more extreme observations than the right tail. Kurtosis ranges from 5.3 in Denmark to 16.3 in Hungary. In all cases, kurtosis is above 3, which is the expected value for a normal distribution. Thus, all daily return distributions are leptokurtic, meaning that relative to normal distributions, they have both higher peaks and fatter tails (a higher probability of extreme values). The non-normality of the daily returns distributions is also confirmed by Jarque-Bera, Shapiro-Wilk and Shapiro-Francia tests, at least at a 1% significance level, for all countries.

4. Methodologies

The approach we use in this paper is to analyze daily returns of stock market indexes, comparing the daily returns on specific calendar periods, such as the day of the week and the month of the year, with the daily returns of the remaining days, outside the period under scrutiny. Calendar effects can be studied either using observations of returns of individual stocks of a specific country, or by examining the behaviour of a stock market index (as in French, 1980, Keim and Stambaugh, 1984, Rogalski, 1984, Chang et al, 1983, Basher and Sodorsky, 2006). Officer (1975) claims that calendar effects are more easily detected in market indexes or large stock portfolios than in individual stock prices.

4.1. Discussion of the model specification

When using stock market indexes, a common approach in the literature consists in estimating the following formula. We present the case for the study of the day of the week effect, coding Monday as 1, Tuesday as 2, Wednesday as 3, Thursday as 4 and Friday as 5:

$$r_t = \alpha + \beta_2^* D_{2t} + \beta_3^* D_{3t} + \beta_4^* D_{4t} + \beta_5^* D_{5t} + \varepsilon_t \qquad (2)$$

Where r_t is the daily return of the stock market index, D_{it} are dummy variables which take on the value of 1 if the corresponding return for day t is a Tuesday, Wednesday, Thursday or Friday, respectively and 0 otherwise. Because the dummy for Monday is missing, the constant α captures the mean return on Mondays; β^*_i are coefficients which represent the mean excess daily returns on the remaining days of the week, relative to Mondays; finally, ε_t is the error term.

In this specification, the *t*-tests of the β^*_i coefficients inform us if they are statistical significant, i.e., if the excess daily returns on Tuesdays, Wednesdays, Thursdays and Fridays, either positive or negative, are significantly different from Mondays' mean return. If we hold an *a priori* belief that an effect exists on one of the specific days, say Monday, this is the best specification. However, if we have no previous expectation on which of the days a calendar effect might exist (or not), the above specification is no longer appropriate. For example, if we want to investigate whether a Thursday effect exists, in the above specification, the coefficient β^*_4 would inform us if Thursdays' returns are statistically different from Mondays' returns, but the model tells us nothing whether Thursdays are different from Tuesdays', Wednesdays' and Fridays' returns. This shortcoming can be overcome by estimating five different models, one for each day of the week, in each case omitting the dummy variable for the day of the week under scrutiny.

But if our purpose is to test a Monday effect, it might be more appropriate to test the mean daily return of that day against the mean daily return of the pool of all non-Monday days, instead of testing Mondays separately against each of the other weekdays. We believe it makes more sense to recognize a Monday effect, if we find out that the mean daily return of that day differs significantly from the mean daily return of non-Mondays, rather than in the case where we find out that Mondays differ from Wednesdays and Thursdays, but not from Tuesdays and Fridays. If, for example, only the coefficient β^*_4 in equation (4) is found to be significant, did we find a Monday effect, or a Wednesday effect?

An alternative specification is to include the dummy variables for all weekdays (all five of them) while excluding the intercept, in order to avoid the dummy variable trap,

$$r_t = \beta_1 D_{1t} + \beta_2 D_{2t} + + \beta_3 D_{3t} + \beta_4 D_{4t} + \beta_5 D_{5t} + \varepsilon_t \qquad (3)$$

In this case, the β_i capture the mean daily return for each of the days of the week, but the *t*-tests for those coefficients only inform us if they are significantly different from zero. If the time period under study is sufficiently long, it is to be expected that mean daily return is positive, whilst a very small number[2]. Therefore, the significance of the *t*-tests is biased in favor of accepting positive excess returns, and against accepting negative excess returns. This specific bias can be corrected if we construct our data set with excess daily returns, instead of daily returns.

However, there would still remain a bias, if the excess returns are constructed by deducting the mean daily returns for the all sample. For example, the excess return on Mondays would not be relative to non-Mondays, but rather relative to all days of the week including Mondays. A simple example illustrates this. Suppose we have the same number observations for each of the days of the week, and that the mean returns for Mondays through Fridays are: 0.001, 0.02, 0.02, 0.02 and 0.02, respectively.

[2] In this paper, we study calendar effects in eighteen European countries, between 1994 and 2007. From table 1, we can see that the mean daily returns for that fourteen-year period ranges between a maximum of 0.0008868 (in Sweden and Iceland) and a minimum of 0.0001556 in the United Kingdom.

The overall mean return is 0.0162, while the mean return for Non-Mondays is 0.02 and the mean return including Mondays but excluding one other day of the week is 0.01525. By deducting the overall mean return, we have the following excess returns: -0.0152 for Mondays and 0.0038 for all other weekdays. By deducting the other-day means returns, we obtain the following excess returns, instead: -0.019 for Mondays and 0.00475 for all other weekdays. By using the overall mean daily return to calculate excess daily returns, we would underestimate the absolute value of the excess returns relative to other days, thus biasing the analysis against the detection of existing calendar effects.

We claim that a simpler approach, which overcomes all these shortcomings, is to estimate five equations separately, each aiming to detect a specific day of the week effect:

$$r_t = \alpha + \beta_i D_{it} + \varepsilon_t \tag{4}$$

With this specification, if we include only the dummy variable for Mondays, α captures the mean daily return of non-Mondays, and β_1 is the excess return of Mondays, relative to non-Mondays. The t-test of β_1 tells us if this effect is significant. The same arguments apply to β_2, β_3, β_4 and β_5, for detecting other days of the week effects. Note that an OLS regression of this equation is formally identical to performing a two-group mean comparison test between the mean daily return of a specific weekday and the mean daily return of all other weekdays.

All the previous discussion can be transposed to month effect analysis, where the only difference is that we need twelve different dummies, M_i (i=1 to 12), each taking on the value of 1 if the corresponding return for day t is of January, February, through December, respectively and 0 otherwise. With this approach, month effect analysis is more burdensome, because we need to estimate twelve separate equations, one for each month:

$$r_t = \alpha + \beta_i M_{it} + \varepsilon_t \tag{5}$$

This model specification is so general, that any specific calendar effect can be studied this way, like for example, the trading days after holidays, the trading days between Christmas and New Year, the first five trading days of each month, the first one hundred days after a new President elected, and so on. We just need to construct the dummy variable to take the value of 1 in the relevant days.

4.2. Estimation procedures

The first studies of calendar effects (French, 1980, Gibbons and Hess, 1981, Jaffe and Westerfield, 1985) employ the linear regression model (OLS) which assumes that the data are normally distributed, serial uncorrelated and with constant variance (Wooldridge, 2003). Connolly (1989, 1991) points out several specific problems that may arise when using this approach: (i) the stock market index returns are likely to be autocorrelated (ii) the residuals are possibly non-normal; (iii) and the variance of the residuals may not be constant.

It is a well documented fact that financial market returns suffer time-dependent changes in volatility (Fama, 1965, Lau et al., 1990, Kim and Kon, 1994). Engle (1982) proposes the use of autoregressive conditional heteroskedasticity (ARCH) models in order to correct the variability in the variance of the residuals. These models assume that the variance of the residuals $\left(\sigma_t^2\right)$ are not constant over time an that the error term can not be modeled $\varepsilon_t \approx iid\left(0, \sigma_t^2\right)$, as assumed in OLS regressions. The generalized version of these models (GARCH) is developed by Bollerslev (1986), where the variance of the residuals is expressed as the sum of a moving-average polynomial of order *q* on past residuals (the ARCH term) plus an autoregressive polynomial of order *p*, on past variances (the GARCH term):

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \lambda_i \sigma_{t-i}^2 \tag{6}$$

The simplest form is GARCH (1,1), which is estimated by maximum likelihood, and includes only one lag both in the ARCH term (last period's volatility) and in the GARCH term (last period's variance). In more recent studies, different versions of the GARCH model have been used by several authors in the study of calendar effects (Choudry, 2000 and Chen et al., 2001). Choudry (2000) applies the GARCH model to a research on a day of the week effect in seven East Asian countries. By analyzing the estimated coefficients of the dummy variables and coefficients, he finds significant effects in three of those countries, and also in ARCH and GARCH terms.

In this paper, we aim to detect calendar effects in the following cases, with no *a priori* restriction on which periods those effect might be revealed: (i) month effects and (ii) day-of-the-week effects. We first address the problem of heteroskedasticity by regressing the models in Stata 10 software, with the option of robust standard errors switched on. The non-normality of the data is tackled by applying the non-parametric bootstrap approach, with 1000 replications for each model regression, and then using the standard errors and confidence intervals resulting from the distribution of the estimated coefficients. The use of the bootstrap approach in the study of calendar effects has been applied before (Sullivan, Timmermann and White, 2001). We perform a test of ARCH effects on our data, and confirm that it is present in the data for all seventeen countries. Therefore we re-estimate all our models with the GARCH(1,1) approach.

5. Results

Considering the discussion in the previous section, we use the following procedures to detect calendar effects in the daily returns of all seventeen stock market indexes, in the period 1994 to 2007. All statistical tests and estimations are computed in Stata 10 software.

5.1. OLS regressions

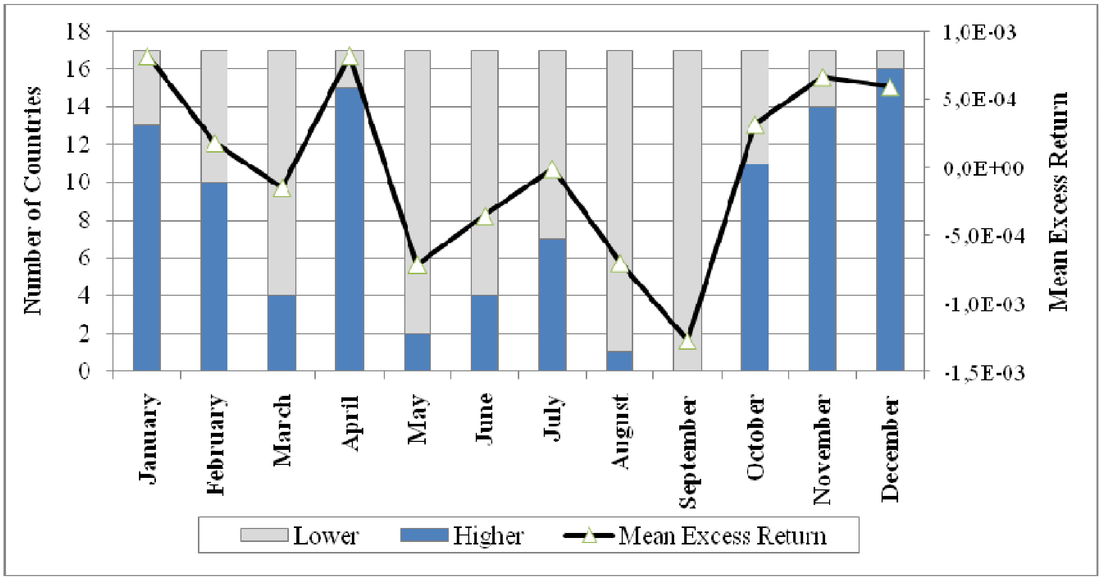
We start by computing individual OLS regressions for each of the seventeen countries, using model (4) for day of the week effects and (5) for month effects. Therefore, we perform a total of 85 regressions for day of the week effects and 204 regressions for month effects. Given the non-normality of the data, all OLS regressions were computed with robust standard errors. The results for the β_i coefficients are presented in Table 2.

INSERT TABLE 2

One of the important critiques to previous studies of calendar effects, is that it may well be exclusively a result of data mining (Sullivan, Timmermann and White, 2001), based on the idea that if we squeeze a particular sample or time series hard enough, all sorts of regularities may start to appear. To control for data-snooping, Cooper, McConnell and Octchinnikov (2006) propose a randomized-bootstrap procedure, and Schwert (2003) suggests the use of data from other countries.

Our first results, in Table 2, are not immune to the critique of Sullivan, Timmermann and White (2001). In day of the week effects, the number of significant coefficients is 2 at the 1% significance level, 6 at the 5% and 5 at the 10%. Given that we compute 85 regressions, the number of significant coefficients that we might expect to find, in random data, would be around 1 (at 1%), around 4 (at 5%) and around 8 (at 10%). So, our overall results for day of the week effects are not very different from those we might expect to obtain, in a randomly constructed sample. For month effects, the number of significant coefficients is 6 (at 1%), 10 (at 5%) and 18 (at 10%). As we have 205 regressions, again, our global results are similar to the number of significant coefficients we might expect to find in random data at 5% (10) and 10% (20). However, at the 1%, we expect to find around 2 significant coefficients in random data, but we have 6. Also, as becomes apparent in Figures 2 and 3 below, there is some concentration of the significant coefficients in specific months and days of the week, and this also justifies further investigation.

Figure 2
Number of Countries with Higher and Lower Daily Returns by Month



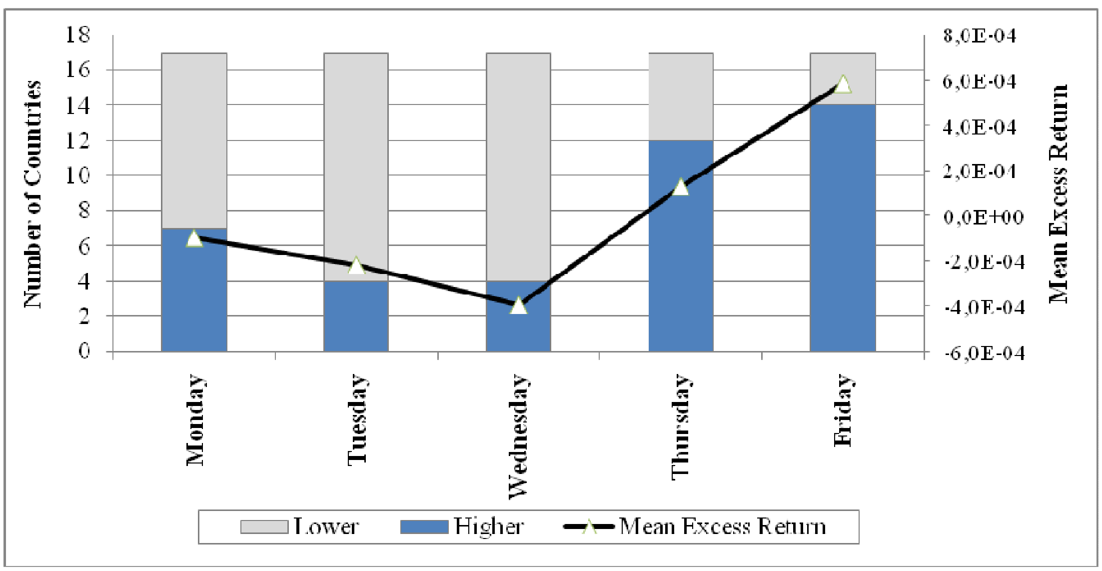
What are the detected month effects? First, January returns tend to be higher than in other months, but are only significant, at 5%, in four (Hungary, Iceland, Poland and Portugal) of the seventeen countries. Second, for most countries, daily returns tend also to be higher in April (but not significant at 5% level) and in the last three months of the year, October, November and December (but only significant in one or two countries). Third, all countries show lower returns than average in August (except Iceland, where it is one of the stronger months) and September. The stronger across-the-board month effect in European countries is clearly September, with significant negative excess returns for two countries at 1%, four countries at 5%, and another four countries at 10%.

The fact that all seventeen countries show negative excess returns in September needs to be addressed. If no month effects existed, the probability that in any given month excess returns are negative is 0.5, for any country. If we assume independence between the seventeen stock markets, the probability that all countries have negative excess returns in the same month is 0.5^{12} = 0.0244%. As there are 12 months, the probability of getting this result in our study would be small, i.e., 0.0244% x 12 = 0.293%. However, we know that most of these stock markets are strongly correlated with each other, and so the independence assumption does not hold. Therefore, contemporaneous movements in all stock markets are expected to happen, and are not necessarily evidence of an investor behavior based month effect.

Taken together, the lower daily returns on August and September justify further investigation of the reasons behind that behavior. Although that is behind the scope of this paper, we propose that the part of the answer might possibly be related to changing behavior of both personal and institutional investors (postponing investment decisions?) related to the enjoyment of summer holidays. As we collect no proof of this, readers should consider this only as suggestion for further investigation.

Figure 3 illustrates the results for day of the week effects.

Figure 3
Number of Countries with Higher and Lower Daily Returns by Weekday



Overall, the individual coefficients for daily excess returns are not significant, but Figure 3 shows that mean excess returns tend to be negative and decreasing in the first three days of the week, in most countries, while excess returns are positive in Thursdays and Fridays, in most countries. The last day of the week seems to be, in average, the strongest day of the week. However, only five countries (Finland, Greece, Iceland, Ireland and Norway) have excess mean returns on Fridays which are significantly different from other weekday returns, at the 5% level.

5.2. Bootstrap Approach and GARCH Model

To test the robustness of the results presented in section 5.1, bootstrapping can be applied to the OLS regressions, as Sullivan, Timmermann and White (2001) propose. These authors warn against the dangers of data mining in the study of calendar effects, claiming that most of the obtained results are only "chimeras" and the product of data mining. We use the bootstrap command in Stata 10, with 1000 replications, to all the OLS regressions. This methodology executes the OLS regressions 1000 times, bootstrapping the statistics of the β_i, by re-sampling observations (with replacement) from the data. Because this is a non-parametric approach, it is not affected by the non-normality of the data.

Additionally, because we know that there are ARCH effects in our sample daily returns, we re-estimate the models for month and weekday effects using the ARCH command in Stata 10, allowing for a GARCH(1,1) process, by means of maximum likelihood. In all estimations, both the ARCH term and the GARCH are significant at the 1% level, confirming that periods of high and low volatility in the residuals are grouped.

As additional evidence, we compute a Kruskal-Wallis equality-of-populations rank test, by dividing daily returns in different groups (months or days of the week), and determining if the null hypothesis that all groups come from the same population. This is similar to a one-way analysis of variance with the data replaced by their ranks. Because this a non-parametric test, it does not depend on the data being normally distributed. The null hypothesis (no effects) is rejected in weekday effects for Greece, Iceland and Poland, and in month effects for Austria, Iceland and Portugal.

Except for the Kruskal-Wallis test, we do not show the obtained results for the bootstrap approach and GARCH (1,1) directly, to avoid burdensome tables. We choose to report exclusively, in Table 3, which day of the week effects remain significant, at a level of 5%, for each of the statistical methodologies applied.

INSERT TABLE 3

In day of the week effects, the following days/countries are significant in all statistical methodologies: (i) positive Fridays in Greece, Iceland, Ireland and Norway; (ii) positive Tuesdays in Germany, and (iii) negative Mondays in Iceland. The GARCH model additionally uncovers: (i) negative Tuesdays in Poland and Greece; and, (ii) negative Mondays in Greece. Overall, the two countries who reveal a stronger day of the week effect are clearly Iceland and Greece, consistently with the weekend effect extensively documented in the literature. Nevertheless, our overall results are very clear in demonstrating that there is no across-the-board weekend effect in European stock markets, as in most countries it is non-existing (including Austria, Denmark, France, Hungary, Italy, Poland, Portugal, Spain, Switzerland and United Kingdom).

Table 4 reports on month effects detected by all the statistical methodologies applied.

INSERT TABLE 4

As in day of the week effects, we find no overall effect covering the full spectrum of countries under study, as there are no month effects in Denmark, Finland, Ireland and UK, and the effects initially detected in some countries do not resist to more robust statistical methodologies, such as France, Hungary, Italy, Netherlands, Norway, Poland, Spain and Switzerland. On the other hand, the stronger month effects include: (i) Iceland has positive excess returns in August, and negative in October; (ii) Austria has positive excess returns in February and negative in September; (iii) Portugal has positive excess returns in January, and negative in May; and, (iv) Greece has negative excess returns in June.

In our sample, Iceland is clearly the country with stronger calendar effects, revealed both on days of the week and months.

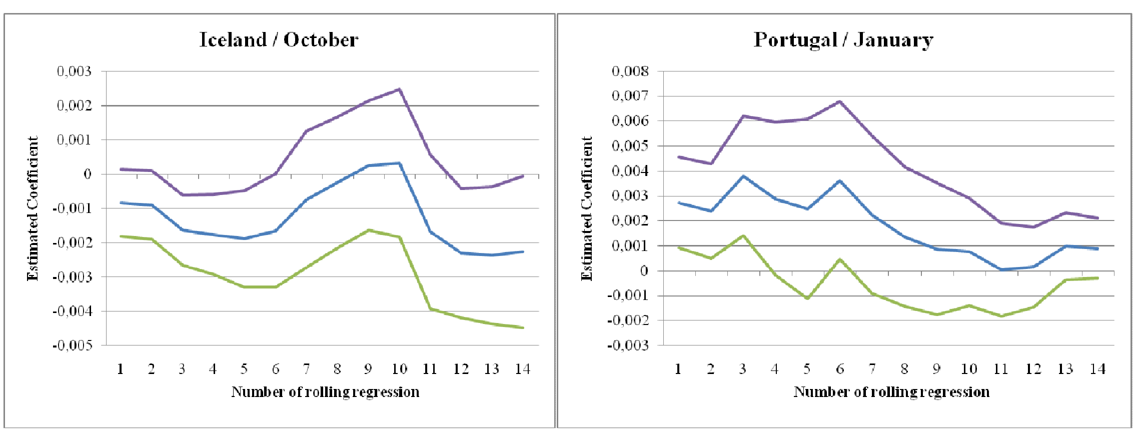
5.3. Time-stability of day of the week and month effects

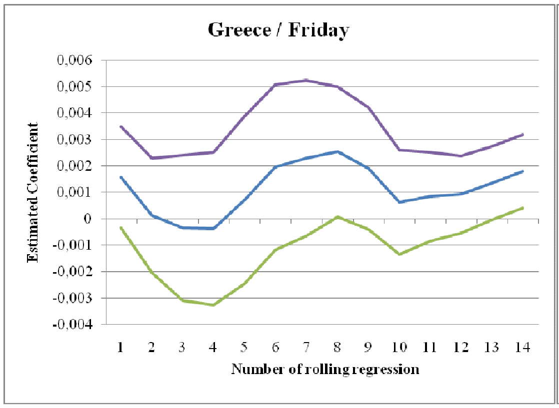
Our sample covers a period of fourteen years, between 1994 and 2007. As an additional robustness check, we investigate if the calendar effects detected are stable, over the whole period under analysis. It may be the case that the global result is affected by short-run phenomena, in only a few of the years under study. The purpose of this section is to shed some light on this.

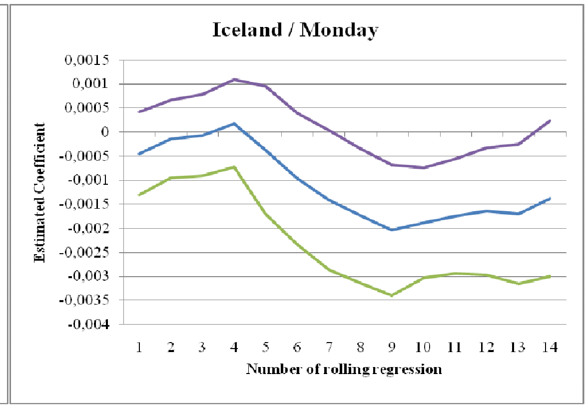
To test the time stability of the coefficients, we compute rolling window OLS regressions on the most significant coefficients detected in day of the week and monthly effects, both for positive and negative excess returns. We choose four cases: (i) for positive day of the week: Greece/Friday; (ii) for negative day of the week: Iceland/Monday; (iii) for positive month: Portugal/ January; (iv) and for negative month: Iceland/October. In the rolling window OLS regressions, we use a window size of 1000 observations (roughly equivalent to four or five years of observations), and a step size of 200 observations. This means that the first regression uses observations [1;1000], the second regression uses observations [201;1200] and so on. Given the number of observations available, we compute 14 rolling regressions for each coefficient. In Figure 4, we show the evolution of the β_i coefficients for these four strong calendar effects, and also the upper and lower bounds on its 95% confidence interval.

Figure 4

Coefficients for Calendar Effects in Rolling-Window Regressions







In all four cases, the coefficient that captures the calendar effect fluctuates significantly, as the windows of observations evolve. In the case of Iceland/October, the coefficient becomes positive both in the 9^{th} and 10^{th} regression, decreasing again sharply after that. In more than half the regressions, the upper bound on the 95% confidence interval is a positive return. In the case of Portugal, the January effect seems to be due mainly to the observations in the first years in the sample, as the effect wears out in the last eight windows of observations. In the case of Greece, the Friday effect changes radically from window to window, with periods of higher returns shortly followed by periods of lower returns. It is only in the last window that the lower bound of the confidence interval is clearly positive. Finally, the Monday effect in Iceland seems to be only a recent phenomenon, as it did not exist in the first windows of observations.

Taken together with the results of the previous sections, this evidence of high instability of the calendar effects coefficients casts further doubt on the significance of the month and day of the week effects in European stock markets.

6. Conclusions

There is an extensive body of research documenting day of the week and month of the year effects, particularly in US markets, although international evidence is constantly growing, but with mixed results. Some studies reveal that calendar effects that were strong in the 1970s, 1980s and 1990s, have become weaker in more recent years, both in developing and developed markets. Is it the case that markets are becoming more efficient and calendar effects are being arbitraged away, or is it the case that more recent and more powerful statistical methodologies no longer detect those effects, casting doubt on previous studies?

There is more than one reason why the findings of previous studies may need to be re-assessed. First, as we discuss in section 4 of this paper, model specifications may have been inadequate for the detection of calendar effects, in particular the use of *t*-tests on models with multiple dummy variables. Second, given the non-normality and other problems in the data, the use of linear regressions may have lead to the incorrect rejection of the null hypothesis of no calendar effects. Third, a large number of studies cover only one country or only a few countries, causing some authors to assign a disproportionate importance to a specific detected effect, which may well be a spurious result delivered by intensive data mining. Studies covering a large number of countries help authors to maintain a skeptical point-of-view on country-specific effects, and these types of studies are still in minority. Fourth, markets develop over time, and widespread knowledge of some types of calendar effects may have lead to their exploitation by arbitrageurs, thus eroding such effects. So, investigators need to look at new and more recent data, frequently enough, and to keep checking the time-stability of previous results.

In our study, we apply robust statistical methodologies and consider only the calendar effects that are significant under all alternative methodologies. Our main findings are the following.

First, we find no strong convincing evidence of an across-the-board calendar effect in West and Central European countries. In particular, there are no statistically significant across-the-board January effects or weekend effects. European countries seem to be mostly immune to day of the week effects, even though the group of seventeen countries, taken together, does tend to show higher daily returns on Thursdays and Fridays, and lower in Mondays in Tuesdays. If any, the only across-the-board calendar effect that warrants further investigation is the general tendency for lower returns in the holiday months of August and September. All the calendar effects are basically country-specific.

Second, the number of significant coefficients we detect is very similar to the number we would expect to find in random data. Even though there is some concentration on specific months / days of the week, our results are not immune to the critique that the calendar effects we detect are exclusively a result from intensive data mining. This skeptical view is reinforced by the fact that the statistically stronger calendar effects are not stable over time. In fact, when we use different sub-samples of the data, the stronger calendar effects that we detect in the whole sample, are not detected in several of those sub-samples. So, some of the apparently stronger calendar effects may well not be the result of economic motives, market microstructure, or behavioral traits, but may rather be only lucky snapshots of capricious movements in the stock market indexes.

Finally, we suggest as avenues for further research, the following. First, some preliminary results we obtain on day of the month effects, which we do not report, signal that this may be the type of calendar effect more relevant in European countries, justifying specific research. Second, the use of data on firms instead of indexes, allows the study of calendar effects by firm characteristics. Third, we need more studies using broader sets of countries, to determine if calendar effects are across-the-board or only country-specific. Fourth, a closer look at the low August / September returns in Europe, and the study of the reasons behind that effect, if it is confirmed. Fifth, there are several alternative variants of the GARCH model, like TGARCH and IGARCH; which one fits the data better? Sixth, we need to improve on the microeconomics of calendar effects. We should strive to find the true economic (or behavioral) rationale behind calendar effects. We need to a better understanding on why calendar effects are expected to exist, and under what circumstances.

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Table 1

Descriptive Statistics for Daily Returns (1994-2007)

Country	Index	Observa-tions	Mean	Standard Deviation	Standard Error of Mean	Maximum	Minimum	10^{th} Percentile	90^{th} Percentile	Skewness	Kurtosis
Austria	**ATX**	3318	0.0003136	0.0104380	0.0001812	0.05135	-0.08427	-0.01098	0.01185	-0.7388	7.8385
Denmark	**OMXC20**	3418	0.0003746	0.0108016	0.0001848	0.04970	-0.06258	-0.01211	0.01278	-0.3467	5.3195
Finland	**OMXHPI**	3404	0.0004392	0.0191563	0.0003283	0.14563	-0.17425	-0.02056	0.02024	-0.5260	10.797
France	**CAC40**	3462	0.0001716	0.0132970	0.0002260	0.07002	-0.07678	-0.01522	0.01475	-0.1227	5.7002
Germany	**DAX**	3465	0.0002944	0.0144468	0.0002454	0.07270	-0.09431	-0.01644	0.01623	-0.2084	6.1468
Greece	**ASE**	3595	0.0004321	0.0151520	0.0002527	0.07661	-0.09615	-0.01527	0.01640	-0.0804	7.5173
Hungary	**BUX**	3391	0.0008001	0.0169282	0.0002907	0.13616	-0.18033	-0.01604	0.01853	-0.8530	16.274
Iceland	**OMXIPI**	3353	0.0008868	0.0076047	0.0001313	0.06970	-0.07053	-0.00650	0.00872	-0.3603	11.543
Ireland	**ISEQ**	3421	0.0003270	0.0100765	0.0001723	0.05835	-0.06124	-0.01082	0.01100	-0.4229	6.8666
Italy	**MIBTEL**	3462	0.0001890	0.0123341	0.0002096	0.06832	-0.10648	-0.01411	0.01416	-0.4008	7.2839
Netherlands	**AEX**	3498	0.0002164	0.0134391	0.0002272	0.09517	-0.07531	-0.01409	0.01395	-0.1519	7.6900
Norway	**OSEAX**	3428	0.0004033	0.0114155	0.0001950	0.08016	-0.06352	-0.01254	0.01286	-0.4416	7.1434
Poland	**WIG**	3279	0.0002076	0.0173266	0.0003026	0.07893	-0.11344	-0.01793	0.01931	-0.5573	8.4188
Portugal	**PSI20**	3389	0.0002643	0.0098439	0.0001691	0.06941	-0.09590	-0.00986	0.00986	-0.7989	11.346
Spain	**IBEX**	3398	0.0003309	0.0128992	0.0002213	0.06323	-0.07339	-0.01483	0.01483	-0.2756	5.8470
Switzerland	**SMI**	3435	0.0002231	0.0115262	0.0001967	0.07462	-0.07331	-0.01256	0.01273	-0.2068	7.3045
UK	**FTSE**	3595	0.0001556	0.0104980	0.0001751	0.05903	-0.05885	-0.01189	0.01168	-0.2053	6.0160

Table 2 (a)
Differences in Mean Returns: Month Effects and Day of the Week Effects (1994-2007)

	Austria	Denmark	Finland	France	Germany	Greece	Hungary	Iceland	Ireland
Month Effects									
January (m1)	0.0008370	0.0006718	-0.0000672	0.0004758	0.0004642	0.0012756	0.0030919***	0.0014591***	0.0005312
February (m2)	0.0012117*	0.0000033	-0.0005953	-0.0003238	-0.0001027	0.0000724	-0.0006621	0.0006754	0.0001269
March (m3)	-0.0001552	-0.0004547	-0.0001447	0.0005065	0.0000163	-0.0003734	-0.0005116	-0.0001510	-0.0001220
April (m4)	0.0011506*	-0.0000662	0.0019942	0.0013475	0.0008637	0.0012275	0.0007798	0.0000061	0.0003006
May (m5)	-0.0002729	0.0000892	-0.0016483	-0.0009067	-0.0005842	-0.0003769	-0.0014368	-0.0005309	-0.000579
June (m6)	-0.0002558	-0.0002900	-0.0003972	-0.0002228	0.0003801	-0.0018381**	0.0001130	-0.0002897	-0.0003666
July (m7)	-0.0002316	0.0004002	-0.0006373	-0.0005493	0.0000795	0.0011410	0.0006777	-0.0000392	-0.0005222
August (m8)	-0.0009997	-0.0000412	-0.001093	-0.0012453	-0.0015085*	-0.0008802	-0.0010083	0.0012296***	-0.0000880
September (m9)	-0.0014473**	-0.0011481*	-0.0003406	-0.0019372**	-0.0023202***	-0.0002694	-0.0017642*	-0.0003333	-0.0010632*
October (m10)	-0.0009800*	0.0000347	0.0017162	0.0012442	0.0006597	-0.0009277	-0.0001182	-0.0010512**	0.0004554
November (m11)	0.0004969	0.0004069	0.0015542	0.0011597	0.0018291**	0.0003771	-0.0007940	-0.0010134**	0.0006287
December (m12)	0.0010656*	0.0004432	-0.0004157	0.0005599	0.0004149	0.0006386	0.0019474*	0.0001833	0.0008309
Weekday Effects									
Monday (d1)	0.0003267	0.0002133	0.0003584	-0.0001953	0.0001200	-0.0011393*	0.0010105	-0.0010800***	-0.0007305*
Tuesday (d2)	-0.0000216	-0.0001378	-0.0013173	0.0001918	0.0012919**	-0.0009483	-0.0002630	-0.0002404	-0.0000191
Wednesday (d3)	-0.0005173	0.0000549	-0.0010811	-0.0003940	-0.0002125	0.0002494	-0.0006958	-0.0003118	-0.0002824
Thursday (d4)	0.0007971*	0.0001466	0.0004348	0.0000647	-0.0006418	0.0002865	-0.0009669	0.0004697	0.0001105
Friday (d5)	-0.0005772	-0.0002778	0.0016806**	0.0003375	-0.0005415	0.0015450**	0.0009558	0.0011560***	0.0008772**

Notes: *Denotes significance at the 0.1 level. **Denotes significance at the 0.05 level. ***Denotes significance at the 0.01 level.

Table 2 (b)
Differences in Mean Returns: Month Effects and Day of the Week Effects (1994-2007)

	Italy	Netherlands	Norway	Poland	Portugal	Spain	Switzerland	UK
Month Effect								
January (m1)	0.0012869*	-0.0003875	0.0006695	0.0023601**	0.0018092***	0.0002735	-0.0004143	-0.0004209
February (m2)	-0.0001054	0.0002576	-0.0000159	0.0010675	0.0008848*	0.0008105	-0.0002606	0.0000201
March (m3)	0.0005654	-0.0004310	-0.0000091	-0.0006989	-0.0000436	-0.0007650	0.0003083	-0.0000293
April (m4)	0.0009929	0.0013887	0.0010869	0.0009733	-0.0006660	0.0009011	0.0009134	0.0007768
May (m5)	-0.0013138*	-0.0002559	-0.0002246	-0.0020804*	-0.0011030*	-0.0003470	0.0000091	-0.0005743
June (m6)	-0.0008792	-0.0001735	0.0000732	-0.0000233	-0.0008001	-0.0006307	0.0000303	-0.0005211
July (m7)	-0.0001825	-0.0000570	0.0003118	0.0007452	-0.0002300	-0.0007125	-0.0004382	0.0000865
August (m8)	-0.0009048	-0.0007284	-0.0009551	-0.0002820	-0.0009143	-0.0011146	-0.0012106*	-0.0002095
September (m9)	-0.0012298*	-0.0020503**	-0.0018248***	-0.0016862	-0.0012040**	-0.0009877	-0.0010732	-0.0009836
October (m10)	-0.0001614	0.0008677	0.0004716	-0.0002076	0.0008932	0.0008898	0.0007582	0.0008577
November (m11)	0.0014259*	0.0011520	0.0002235	-0.0002220	0.0007718	0.0016059**	0.0012480*	0.0004334
December (m12)	0.0007903	0.0006395	0.0003714	0.0008053	0.0006780	0.0003548	0.0002129	0.0005978
Weekday Effect								
Monday (d1)	-0.0005973	0.0005714	-0.0001770	0.0008422	-0.0003908	-0.0006186	-0.0000761	-0.0000452
Tuesday (d2)	0.0000217	-0.0001557	-0.0004651	-0.0016038**	-0.0000050	0.0002262	-0.0001401	-0.0001057
Wednesday (d3)	-0.0003295	-0.0004713	-0.0007308	-0.0010887	0.0001411	-0.0005240	0.0000865	-0.0005845
Thursday (d4)	0.0002900	-0.0003432	0.0004058	0.0012438*	-0.0001887	0.0000621	-0.0001172	0.0001690
Friday (d5)	0.0006044	0.0004175	0.0009807**	0.0007086	0.0004365	0.0008570*	0.0002453	0.0005648

Notes: *****Denotes significance at the 0.1 level. **Denotes significance at the 0.05 level. ***Denotes significance at the 0.01 level.

Table 3
Weekday Effects by Country (At Significance Level: 5%)

Country	Index	Higher Returns than Other Weekdays			Lower Returns than Other Weekdays			Kruskal – Wallis Test
		Regression	Bootstrap /Regression	GARCH Model	Regression	Bootstrap /Regression	GARCH Model	
Austria	**ATX**	-	-	-	-	-	-	0.3485
Denmark	**OMXC20**	-	-	-	-	-	-	0.9661
Finland	**OMXHPI**	Friday*	Friday*	-	-	-	-	0.1232
France	**CAC40**	-	-	-	-	-	-	0.9454
Germany	**DAX**	Tuesday*	Tuesday*	Tuesday*	-	-	-	0.1189
Greece	**ASE**	Friday*	Friday**	Friday**	-	-	Mon**, Tue**	0.0005**
Hungary	**BUX**	-	-	-	-	-	-	0.2635
Iceland	**OMXIPI**	Friday**	Friday**	Friday**	Monday*	Monday**	Monday**	0.0001**
Ireland	**ISEQ**	Friday*	Friday*	Friday*	-	-	-	0.1305
Italy	**MIBTEL**	-	-	-	-	-	-	0.3035
Netherlands	**AEX**	-	-	-	-	-	-	0.2455
Norway	**OSEAX**	Friday*	Friday*	Friday*	-	-	-	0.0507
Poland	**WIG**	-	-	-	Tuesday*	-	Tuesday*	0.0302*
Portugal	**PSI20**	-	-	-	-	-	-	0.8178
Spain	**IBEX**	-	-	-	-	-	-	0.2686
Switzerland	**SMI**	-	-	-	-	-	-	0.9568
UK	**FTSE**	-	-	-	-	-	-	0.2400

Notes: *Denotes significance at the 0.05 level. **Denotes significance at the 0.01 level.

Table 4
Month Effects by Country (At Significance Level: 5%)

Country	Index	Higher Returns than Other Months			Lower Returns than Other Months			Kruskal – Wallis Test
		Regression	Bootstrap /Regression	GARCH Model	Regression	Bootstrap /Regression	GARCH Model	
Austria	**ATX**	-	Feb*, Apr*	Feb*	Sep*	Sep*	Sep**	0.0383*
Denmark	**OMXC20**	-	-	-	-	-	-	0.9791
Finland	**OMXHPI**	-	-	-	-	-	-	0.7046
France	**CAC40**	-	-	-	Sep*	-	-	0.4088
Germany	**DAX**	Nov*	Nov*	-	Sep**	Sep*	-	0.5714
Greece	**ASE**	-	-	-	Jun*	Jun*	Jun*	0.2311
Hungary	**BUX**	Jan**	Jan*	-	-	-	-	0.0744
Iceland	**OMXIPI**	Jan**, Aug**	Jan**, Aug**	Aug**	Oct*, Nov*	Oct*, Nov*	Oct*	0.0012**
Ireland	**ISEQ**	-	-	-	-	-	-	0.6429
Italy	**MIBTEL**	-	Nov*	-	-	-	-	0.0847
Netherlands	**AEX**	-	-	-	Sep**	Sep*	-	0.5963
Norway	**OSEAX**	-	-	-	Sep**	Sep*	-	0.5902
Poland	**WIG**	Jan*	Jan*	-	-	-	-	0.1285
Portugal	**PSI20**	Jan**	Jan**	Jan**	Sep*	May*	May*	0.0180*
Spain	**IBEX**	Nov*	Nov*	-	-	-	-	0.3301
Switzerland	**SMI**	-	Nov*	-	-	-	-	0.6630
UK	**FTSE**	-	-	-	-	-	-	0.7609

Notes: *Denotes significance at the 0.05 level. **Denotes significance at the 0.01 level.